

A NOVEL APPROACH TO CLASSIFY HEART ARRHYTHMIA USING DEEP LEARNING

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By

Shah Amit Dinesh

Registration Number: 42000504

Supervisor

Dr. Dhanpratap Singh (25706)

Computer Science & Engineering (Professor)

Lovely Professional University



**LOVELY PROFESSIONAL UNIVERSITY, PUNJAB
2026**

DECLARATION

I hereby declare that the work presented in the thesis entitled “A NOVEL APPROACH TO CLASSIFY HEART ARRHYTHMIA USING DEEP LEARNING” in fulfilment of the degree of **Doctor of Philosophy (Ph.D)** is the outcome of research work carried out by me under the supervision of Dr Dhanpratap Singh, working as a Professor in the Department of Computer Science & Engineering at Lovely Professional University, Punjab, India. In keeping with the general practice of reporting scientific observations, due acknowledgements have been made whenever work described here has been based on findings of other investigators. This work has not been submitted in part or in full to any other University or Institute for the award of any degree.

A handwritten signature in dark ink, appearing to read 'Amit Shah', is written over a horizontal line.

(Signature of Scholar)

Name of the scholar: Shah Amit Dinesh

Registration Number.:42000504

Department/school: Computer Science and Engineering

Lovely Professional University,

Punjab, India

CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled “A Novel Approach to Classify Heart Arrhythmia Using Deep Learning ” submitted in fulfillment of the requirement for the award of the degree of **Doctor of Philosophy (Ph.D)** in the Computer Science and Engineering Department, is a research work carried out by Mr. Amit Dinesh Shah Registration Number 42000504, is Bonafide record of his original work carried out under my supervision and that no part of the thesis has been submitted for any other degree, diploma or equivalent course.

A handwritten signature in black ink on a light purple background. The signature is stylized and appears to read 'D. Singh'.

(Signature of Supervisor)

Name of supervisor: Dr Dhanpratap Singh

Designation: Professor

Department: Computer Science and Engineering

University: Lovely Professional University, Punjab, India

ABSTRACT

Cardiovascular disease (CVD) remains one of the leading causes of mortality worldwide and poses a significant public health challenge, particularly in India due to the increasing prevalence of hypertension, diabetes, obesity, sedentary lifestyles, and other cardiovascular risk factors. Electrocardiogram (ECG)-based arrhythmia detection plays a vital role in the early diagnosis of cardiac abnormalities; however, existing automated approaches often suffer from residual noise, morphology distortion during denoising, limited feature representation, and inadequate generalisation under real-time clinical conditions. These challenges reduce the reliability of computer-aided diagnosis and highlight the need for an accurate, robust, and clinically applicable ECG analysis framework.

This research proposes a unified and hierarchical framework for ECG signal denoising and arrhythmia classification by integrating Machine Learning (ML), Deep Learning (DL), and Soft Computing techniques for real-time cardiac diagnosis. The proposed framework employs a Tuned Kalman Filter (TKF) to effectively suppress baseline wander, power-line interference (PLI), and other ECG artifacts while preserving clinically significant waveform characteristics, including the P wave, QRS complex, and T wave. Subsequently, R-peak-based segmentation is performed, and the extracted heartbeat signals are processed using a Self-Attention Autoencoder (SAE) network, which automatically learns discriminative spatial and temporal representations while emphasising diagnostically relevant features through a self-attention mechanism. Unlike conventional ECG classification methods, the proposed framework combines morphology-preserving adaptive denoising with attention-based deep feature learning, resulting in improved robustness and classification performance.

The proposed framework is trained and validated using the MIT-BIH Arrhythmia Database together with real-time clinical ECG recordings collected from participants in Amravati, Maharashtra, India. A stratified 10-fold cross-validation strategy is employed to ensure robust model generalisation, particularly for minority arrhythmia classes. Experimental results demonstrate that the proposed TKF significantly enhances ECG signal quality, improving the signal-to-noise ratio (SNR) from 17.85 dB using conventional notch filtering to 23.20 dB while preserving ECG morphology.

Furthermore, the proposed classification framework achieves an overall accuracy of 99.71% on the benchmark ECG dataset and 98.00% on real-time clinical data, demonstrating its effectiveness for automated arrhythmia detection. As a complementary behavioural component of this research, Om chanting was evaluated as a non-invasive intervention, indicating favourable changes in cardiac rhythm variability and suggesting a potential adjunct role for holistic wellness practices alongside automated diagnosis. The proposed framework adheres to ethical guidelines by ensuring participant anonymity, informed consent, and secure handling of clinical data.

In conclusion, the proposed framework provides an effective, reliable, and clinically relevant solution for real-time ECG denoising and automated arrhythmia classification. By combining adaptive signal enhancement with attention-based deep learning, it addresses several limitations of existing ECG analysis methods while supporting accurate computer-aided diagnosis. The proposed approach also provides a foundation for future research on wearable healthcare devices, edge-AI implementation, Transformer-based architectures, semi-supervised learning, and seamless integration with electronic health records to facilitate intelligent and personalised cardiac healthcare.

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

LOVELY PROFESSIONAL UNIVERSITY

Punjab, India-144411

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(Signature of Scholar)

Name of the scholar: Shah Amit Dinesh

Registration No.: 42000504

Department/School: School of Computer Science and Engineering

Place: Lovely Professional University, Punjab, India

Date: 25.07.2025

Contents

INTRODUCTION.....	5
1.1. Cardiac Arrhythmia	5
1.1.1 Datasets.....	9
1.1.2 Arrhythmia classification challenges	17
1.2. Problem Statement.....	19
1.3. ECG-based arrhythmia identification and classification	20
1.4 Scope of the work	22
1.5 Objectives	23
1.6 Novelty of the Proposed Research.....	24
1.7 Hypotheses Formulation	25
1.8 Research Methodology	27
1.9 Limitations.....	31
1.10 Thesis Organisation	32
1.11 Chapter Summary	33
CHAPTER 2.....	35
BROAD REVIEW OF ARRHYTHMIA CLASSIFICATION METHODS.....	35
2.1 Primary Literature Review	35
2.1.1 Denoising Techniques for ECG Signal	35
2.1.2 ML-Based Denoising Methods.....	35
2.1.3 DL-Based Denoising Methods	37
2.1.4 Soft Computing Approaches for Noise Reduction.....	38
2.2 Classification Techniques for Arrhythmia	42
2.2.1 ML Approaches	42
2.2.2 DL Approaches	44
2.2.3 Soft Computing Approaches.....	46
3 Research Gap Identification.....	51
Gap 1: ECG Signal Denoising	51
Gap 2: Feature Extraction.....	51
Gap 3: Integrated Framework	52
Gap 4: Clinical Validation.....	52
Gap 5: Computational Efficiency.....	52
2.4 Chapter Summary:	52

CHAPTER 3.....	54
ARRHYTHMIA CLASSIFICATION METHODS BASED ON ML/DL TECHNIQUES.....	54
3.1. Literature Analysis Process.....	54
3.2. Secondary Literature Review	57
3.2.1. ECG Analysis	62
3.2.2. ML and DL Techniques	65
3.4 Chapter Summary	82
CHAPTER 4.....	86
RESEARCH METHODOLOGY	86
4.1. Introduction	86
4.2 Research Approach	89
4.2.1 Theoretical Framework.....	90
4.2.2 Research Design	91
4.2.2.1. Signal Denoising (Pre-processing Stage)	91
4.2.2.2 Arrhythmia Classification (Deep Learning Stage).....	99
4.5 Chapter Summary.....	117
CHAPTER 5.....	118
IMPLEMENTATION AND EXPERIMENTAL SETUP	118
5.1 Data Collection	119
5.1.1. Participants / Materials	119
5.1.2 Sampling Strategy	119
5.1.3 Data Collection Methods by MIT BIH Data Set	120
5.1.3.1 Data Collection Methods by Real-Time Data Set	120
5.1.4 Instrumentation	121
5.2. Data Analysis.....	121
5.2.1. Analysis Techniques	122
5.2.1.1. Denoising Evaluation (Signal-Level Analysis)	122
5.2.1.2. Arrhythmia Classification (Model-Level Analysis).....	122
5.2.2.3 Software and Tools	123
5.3 Deep Learning Model Parameter Settings	124
5.4. Validity and Reliability	125
5.4.1 Measures Taken	125
5.4.2 Limitations.....	126

5.4.3 Justification of Chosen Methods	127
5.5 Ethical Considerations	128
5.6 Chapter Summary:	129
CHAPTER 6.....	130
RESULTS AND PERFORMANCE EVALUATION	130
6.1. Evaluation of ECG Denoising under 60 Hz PLI.....	130
6.2. 50 Hz PLI Results.....	133
6.2.1. Real-Time TKF ECG Pre-Processing Results	137
6.3. Performance Optimisation Results and Analysis	140
6.4 Chapter Summary:	145
CHAPTER 7.....	148
COMPARATIVE ANALYSIS AND DISCUSSION	148
7.1. Comparison With Traditional Models	148
7.2. Limitations of the Proposed Framework.....	148
7.3 Chapter Summary:	155
CHAPTER 8.....	156
FEASIBILITY STUDY AND DEPLOYMENT ASSESSMENT	156
8.1 Introduction	156
8.2 Statistical Hypothesis Testing Methodology:.....	158
8.2.1 Hypothesis Formulation.....	159
8.3 Demographic Analysis.....	160
8.3.1 Graphical Demographic Analysis	162
8.5 Descriptive Analysis	174
8.6 Data Reliability and Validity	176
8.6.1 Kaiser-Meyer-Olkin (KMO) and Bartlett's Test	178
8.7 Chapter Summary:	182
CHAPTER 9.....	184
CONCLUSIONS, RECOMMENDATIONS, and FUTURE SCOPE	184
9.1. Conclusions and Recommendations	184
9.2 Clinical Deployment Challenges and Practical Considerations.....	190
9.3 Generalizability to Multicentre Clinical Datasets	193
9.4 Future Scope	194
1. Validation on Large Multicentre ECG Datasets	196
2. Lightweight Deep Learning Model	196
3. Explainable Artificial Intelligence (XAI).....	197

4. Adaptive Signal Denoising.....	197
5. Federated Learning.....	197
6. Multimodal Healthcare Analytics.....	197
7. Real-Time Edge Deployment.....	198
8. Continuous Learning.....	198
9. Clinical Decision Support System.....	198
9.5 Chapter Summary:	198
BIBLIOGRAPHY	200
RESEARCH SURVEY	217
PROJECT TESTING REPORT	220
LIST OF PUBLICATION	222

List of Tables

1.1	Comparative Overview of Public ECG Datasets for Arrhythmia Detection.....	21
1.2	Proposed Research Novelty Work	25
2.1	Comparative Summary of Existing Arrhythmia Classification Studies.....	49
2.2	Research Gap Analysis of Existing Arrhythmia Classification Methods.....	51
3.1	Shortlisted Literature Across Elsevier, Springer, and IEEE Sources	61
3.2	Existing Signal Preprocessing Methods	72
3.3	Comparative Analysis of Existing ML/DL Techniques	83
3.4	Comparison Table	85
3.5	Computational Complexity of Common Algorithms	86
4.1	Hyperparameter Tuning	115
6.1	Proposed MKF Denoising Results with 60 Hz.....	122
6.2	Proposed Notch Filter Denoising Results with 60 Hz.....	124
6.3	Pre- and Post-OM-chanting Patient Analysis for 90-Minute Session.....	127
6.4	Confusion Matrix for Proposed Self-attention AE	133
7.1	State-of-the-art Analysis Signal Denoising	137
7.2	Experimental Results for Self-attention-AE.....	139
7.3	State-of-the-Art Performance Comparison	139
8.1	Decision rule for statistical hypothesis	162
8.2	Sample Size	164
8.3	Gender Analysis.....	164
8.4	Age Analysis.....	165
8.5	Marital Status.....	165
8.6	Work Experience.....	165
8.7	Education.....	165
8.8	Job Status.....	165
8.9	OM Chanting Status	166
8.10	Yoga-pranayama Practice	166
8.11	Five-Point Likert Scale	172
8.12	Classification and prediction of heart arrhythmia.....	173
8.13	Traditional ECG Analysis.....	174
8.14	Analog ECG Signal Interpretation	175
8.15	Comparison of the proposed system and existing system.....	176
8.16	Proposed System Add-on medical facilities.....	177
8.17	Prediction of Sudden cardiac arrest	178
8.18	Descriptive Statistics of Proposed System	179
8.19	Descriptive Statistics and Cronbach's Alpha for Proposed Study.....	153
8.19	Kaiser-Meyer-Olkin (KMO) and Bartlett's Test	182

LIST OF FIGURES

1.1:	Represents The Normal and Arrhythmia-influenced Heart Schematic	3
1.2:	Electronic Arrangement for the ECG Data Collection	6
1.3:	Comparisons Between Computational Methods and DL Methods	15
1.4:	Hierarchical Process of ECG-based Arrhythmia Identification and Classification	17
1.5:	Proposed Research Life Cycle Methodology	24
1.6:	Reliability of participants' graph of the proposed study	26
2.1:	Block diagram of plain wavelet transforms	34
2.2:	Representation of empirical wavelet transforms (EWT)	35
2.3:	Representation of deep convolutional neural network	40
3.1:	Bibliographic Representation of Literature Database	50
3.2:	Representation of the ECG signal interval	56
3.3:	Residual deep learning attention-based model	62
3.4:	Residual deep learning attention-based model	63
3.5:	CAT-Net attention-based model	64
3.6:	BiLSTM attention-based model (Source: MathWorks)	65
3.7:	BiLSTM attention-based model (Berrahou, Nadia, et al., 2025)	66
3.8:	DBSCAN attention-based model	67
3.9:	Savitzky-Golay Filter Function	68
3.10:	Flow diagram of the empirical wavelet transform method	68
3.11:	Flow diagram of the Kalman filter processing	69
4.1:	Taxonomical References for Proposed Methods	73
4.2:	Block Diagram of 50 and 60 Hz PLI Denoising ECG using KF	80
4.3:	Current state prediction with Modified Kalman	83
4.4:	Current state estimate of Modified Kalman Filter	83
4.5:	Predicted State Estimate of Modified Kalman Filter	84
4.6:	Proposed Model Component architecture	86
4.7:	Proposed Methodology Flow	87
4.8:	Proposed Self-attention-AE Model	88
4.9:	Flow of the Sudo Code of AI-Dense Fit	95
4.10:	Flow of the Sudo Code of Self-attention-AE Model	97

6.1:	Clean ECG	107
6.2:	60 Hz input to the system as a noisy ECG	108
6.3:	60 Hz denoising results for ECG notch filter	108
6.4:	Proposed 60 Hz removal denoising results for ECG 100 at 15 dB	109
6.5:	Clean ECG	110
6.6:	Noisy ECG	110
6.7:	Notch Filter	111
6.8:	Proposed 50 Hz removal denoising results for ECG 100 at 15 dB	112
6.9:	Pre-Enchanting Reading	115
6.10:	Post-Enchanting Reading	115
6.11:	Overall cardiac arrhythmia analysis of 40 patients	116
6.12:	Self-attention-AE	117
6.13:	Training and validation model loss for the proposed system	117
6.14:	Classification Error for proposed system	118
6.15:	Reconstruction Error for proposed system	119
6.16:	Recorded precision and recall values	119
6.17:	Confusion matrix for proposed Self-attention-AE model	120
7.1:	Classification of ECG signal for a Single beat sinus	124
7.2:	Confusion matrix for proposed AI-DenseFit model	125
8.1:	Gender	137
8.2:	Age Analysis	137
8.3:	Marital status	138
8.4:	Work Experience	138
8.5:	Education	139
8.6:	Job status	139
8.7:	OM chanting status	140
8.8:	Yoga-Pranayama practice	140
8.9:	400 participants' coordination during the survey	154
8.10:	400 participants' deviation in responses	155
8.11:	Proposed system acceptance test (N=40)	156
8.12:	Proposed system convenience test (N=40)	157

List of Acronyms

A list of acronyms in the thesis is listed below

Sr. No	Acronyms	Full Form
1	AF	Atrial Fibrillation
2	PPG	Photoplethysmography
3	PTB	Physikalisch-Technische Bundesanstalt
4	SA node	Sinoatrial Node
5	AV Node	Atrioventricular
6	LR	Logistic Regression
7	KNN	K-Nearest Neighbours
8	SVM	Support Vector Machine
9	DT	Decision Tree
10	RF	Random Forest
11	XGBoost	Extreme Gradient Boosting
12	Self-attention-AI Auto Encoder	Self-Attention Artificial Intelligence Auto Encoder
13	FIR, IIR filtering	Finite Impulse Response & Infinite Impulse Response
14	PLI	Power Line Interference
15	SDAE	Stacked Denoising Autoencoders.
16	GAN	Generative Adversarial Networks
17	MP-EKF	Multi-Parameter Extended Kalman Filter
18	JRip	Repeated Incremental Pruning to Produce Error Reduction (RIPPER)
19	QoL	Quality of Life
20	AFL	Atrial Flutter
21	ASTA	Arrhythmia-Specific Questionnaire in Tachycardia and Arrhythmia
22	PVC	Premature Ventricular Contraction
23	VT	Ventricular Tachycardia
24	SVT	Supraventricular Tachycardia
25	UKF-MLP	Unscented Kalman Filter – Multilayer Perceptron
26	CHA ₂ DS ₂ -VASc	Congestive Heart Failure, Hypertension, Age, Diabetes Mellitus, Stroke-Vascular Disease, Age, Sex Category
27	mRMR	Minimum Redundancy Maximum Relevance
28	RRHOS-LSTM	Residual Recurrent Hierarchical Optimized Stacked Long Short-Term Memory
29	NSR Dataset	Normal Sinus Rhythm Dataset
30	SCDH Dataset	Sudden Cardiac Death Holter Dataset

LIST OF APPENDICES

List of Publications

- 1 Research Survey
- 2 Doctor Recommendation Letter
- 3 *Journal of Harbin Engineering University* – Denoising of Power Line
Interference at Negative SNR Contaminated ECG signal using Kalman Filter – 2023
- 4 Book Chapter: Data Science and Intelligent Computing Techniques –
Computing & Intelligent System, SCRS, India-A Survey of Heart Disease
Prediction Using Deep Learning Methods- 2023
- 5 8th Int'l Conference on Computing Communication Control & Automation
(ICCUBEA-2024) – Pune
- 6 5th Int'l Conference on Image Processing and Capsule Networks
(ICICN-2024) – Nepal
- 7 *Scientific Reports* – Electrocardiogram Analysis for Cardiac Arrhythmia
Classification And Prediction Through Self-Attention-Based Auto Encoder – 2025

CHAPTER 1

INTRODUCTION

1.1. Cardiac Arrhythmia

An arrhythmia causes the heart to beat slowly, fast, or irregularly when electrical signals that control the heart's rhythm don't work properly. Arrhythmias, or irregular heartbeats, vary in clinical significance, ranging from harmless to life-threatening, depending on their type and severity. Prompt medical attention is warranted when symptoms such as palpitations, dizziness, or shortness of breath as certain arrhythmias increase the risk of stroke, heart failure, or sudden cardiac arrest. When the heart cannot pump blood efficiently, the brain, lungs, and other organs are unable to function normally, potentially leading to organ dysfunction or failure.

Cardiovascular Disease (CVD), a major non-communicable disease, is a leading cause of death worldwide and contributes significantly to mortality in India. Information from numerous departments shows that heart disease contributes to a substantial proportion of these deaths. According to statistics from the World Health Organisation [1-4], approximately 37% of deaths are caused by heart disease alone, with the figure reaching as high as 45% in some European countries. This proportion is predicted to increase within the next few years compared to current conditions.

There are many different possible causes of arrhythmia, including:

- Abnormal heart structures: Arrhythmia results from certain heart structural abnormalities, such as enlarged heart chambers or scar tissue from prior heart attacks.
- Coronary artery disease: This disorder results in arrhythmias when the arteries supplying blood to the heart constrict or get blocked.
- High blood pressure: An arrhythmia results from high blood pressure's strain on the heart.
- Electrolyte imbalances: Arrhythmias result from abnormalities in the body's electrolytes, which include calcium, magnesium, and potassium.
- Thyroid issues: An arrhythmia can result from an overactive or underactive thyroid gland that alters the heart's rhythm.
- Abuse of drugs or alcohol: Abuse of substances causes arrhythmia and damages the heart.
- Sleep apnea: This disorder raises the risk of arrhythmia and results in frequent breathing pauses while you sleep.
- Anxiety or stress: Emotional stress can alter cardiac rhythm and lead to arrhythmia.

Cardiac Arrhythmia

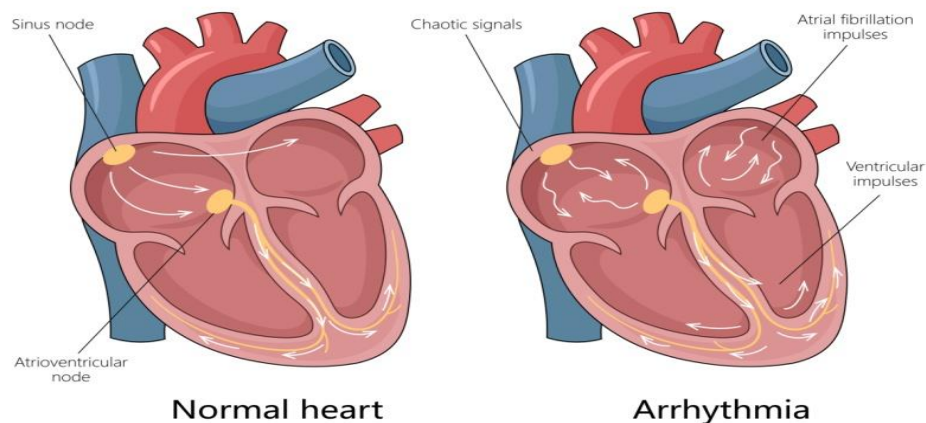


Figure 1.1 Schematic of the Normal and Arrhythmia-Affected Heart [130]

A normal heart schematic shows smooth, regular electrical conduction starting at the SA node, travelling through the atria, AV node, bundle branches, and Purkinje fibres—resulting in a steady sinus rhythm with evenly spaced PQRST waves on ECG. An arrhythmia-influenced heart schematic depicts disrupted conduction—either irregular timing, abnormal pathways, or ectopic foci—which causes an abnormal rhythm (too fast, too slow, or erratic), leading to distorted or missing PQRST patterns on ECG.

There are many risk factors for cardiovascular disease, including genetic predisposition, high blood pressure, high cholesterol, and elevated heart rate, among other contributing factors [5]. Physicians continue to be trained in managing cardiovascular disease based on medical records and case histories interpreted considering the patient's clinical presentation. The burden of the disorder continues to grow, underscoring the urgent need for a predictive technique that draws on high-quality patient health history. Approximately 35% of deaths in India are attributable to cardiovascular disease alone [6].

The electrical impulse originating from the SA node travels through the heart's muscle tissue to initiate the heartbeat, or contraction. Because it initiates heartbeat impulses, the SA node is referred to as the heart's "natural pacemaker." Starting in the right atrium, the typical electrical sequence travels to the Atrioventricular (AV) node via the atria.

The ventricles contract because of electrical impulses that pass from the AV node down the Purkinje fibres and down the bundle of His. Because electrical impulses result in a series of coordinated contractions, the heart beats regularly. An adult's heart beats 60–100 times per minute on average. A straightforward, painless procedure called Electrocardiography (ECG) is used to identify arrhythmias by recording the electrical activity of the heart [7, 8].

Abnormal heartbeats are known as arrhythmias. Any deviation from the typical electrical impulse sequence is referred to as an "arrhythmia." Approximately, arrhythmias are short-term (temporary pauses or premature beats) that can critically affect overall heart rate or rhythm. However, prolonged arrhythmias can cause the heart rate to become too rapid, too slow, or irregular, which reduces the heart's ability to pump blood efficiently. Adults with a rapid heart rate (more than 100 beats per minute) are said to have tachycardia. Bradycardia is the term for a sluggish heart rate [9–11].

A sequence of events, including the outcomes of heart tissue polarisation and depolarisation, is also represented by an ECG signal. The most significant of these events, known as waves, are denoted by letters P, Q, R, S, and T. Apart from the waves, there are also the times in between them. Therefore, the QRS complex is a collection of Q, R, and S waves along with their intervals; the QT interval is made

up of the Q and T waves; and the ST segment is the time between the end of the S wave and the start of the T wave.

The origin and physiological distribution of the electrical stimulation of the heart may be altered by changes in the generation and conduction of electrical impulses across the myocardial tissue, which results in cardiac arrhythmias [12,13]. A heart rhythm disruption, also known as cardiac dysrhythmias, can range in severity from completely benign to arrhythmias that pose an immediate risk to life. Acute arrhythmic death syndrome and other cardiac disorders are closely associated with these irregular heartbeats. Therefore, it is crucial to identify and describe arrhythmias to diagnose heart problems. An essential part of the clinical ECG workflow is the analysis of computerised ECGs. The algorithmic paradigm of deep learning, with the abundance of digital ECG data, offers a chance to significantly increase the scalability and accuracy of automated ECG analysis. However, there hasn't been a thorough assessment of an end-to-end DL method for ECG analysis across a large range of diagnostic classes before [14–16].

1.1.1 Datasets

Several public and widely used ECG datasets are available for arrhythmia research and machine learning, including the MIT-BIH Arrhythmia Database, PTB Diagnostic ECG Database, and Deep-Q Arrhythmia Database [17-20]. Figure 1.2 shows the electronic setup for ECG data collection, including electrode placement, signal amplification, digitisation, and storage for analysis.

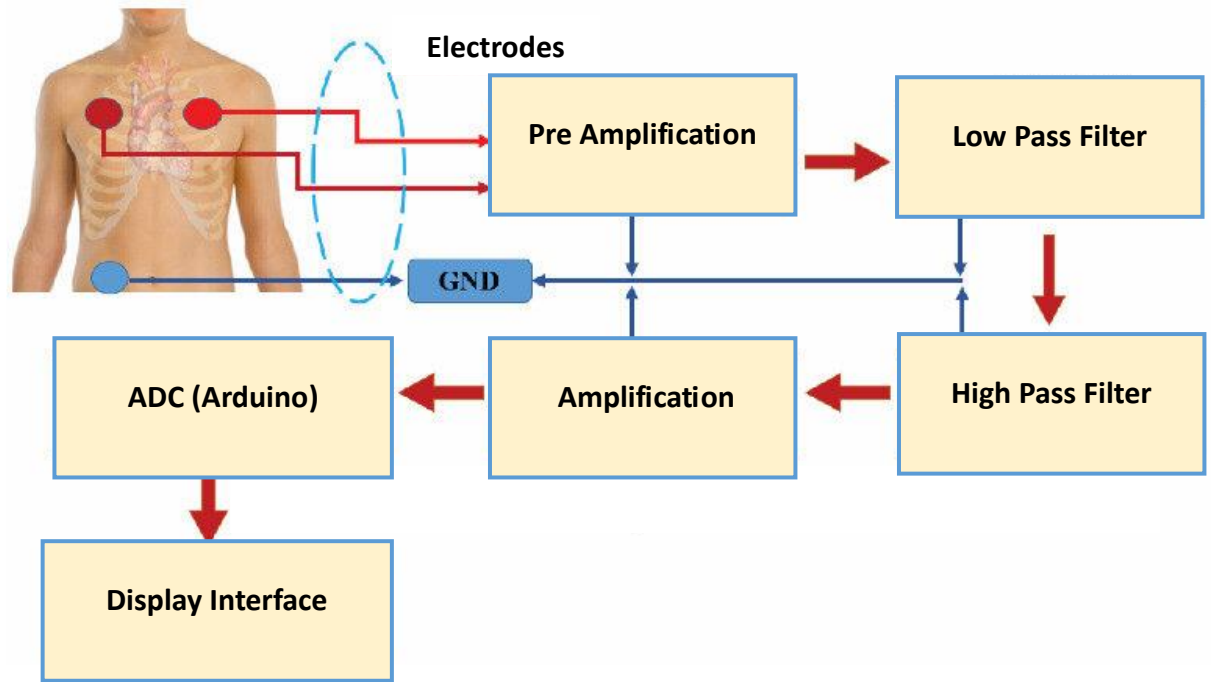


Figure 1.2: Electronic Arrangement for the ECG Data Collection

The purpose and specifications of each dataset are given:

- PTB Diagnostic ECG Database:

This dataset, also available on PhysioNet, is another popular resource for heartbeat classification and arrhythmia detection research.

- DeepQ Arrhythmia Database:

This dataset, available on ACM Digital Library, is a large-scale dataset for arrhythmia detector evaluation, including 897 annotated single-lead ECG recordings from 299 unique patients.

- St. Petersburg INCART 12-lead Arrhythmia Database:

This database, available on PhysioNet, contains 75 annotated 30-minute recordings with 12 standard leads sampled at 257 Hz.

- CACHET-CADB:

Contextualised ECG recordings from 24 patients are included in this dataset, which also continuously records contextual information about the patients, including activities, body postures, movement accelerations, symptoms, stress level, and sleep quality.

- UCSF LAD:

During hospital-based adult patient monitoring, this dataset is intended to evaluate and report on the effectiveness of algorithms for the identification of three different forms of lethal cardiac arrhythmia alarms: ventricular tachycardia, ventricular fibrillation, and asystole.

- ECG Heartbeat Categorisation Dataset:

This dataset, available on Kaggle, contains a variety of ECG heartbeat signals for classification tasks.

- ECG Arrhythmia Image Dataset:

This Kaggle dataset consists of heartbeat signals taken from the PTB Diagnostic ECG Database and MIT-BIH Arrhythmia Dataset in two sets.

- MIT-BIH Arrhythmia Database:

The MIT-BIH Arrhythmia Database is a well-known and widely used resource for arrhythmia detection research, containing 48 half-hour extracts of two-channel ambulatory ECG recordings from 47 subjects. Developed by MIT in collaboration with Beth Israel Hospital, the dataset was created to support the evaluation and benchmarking of arrhythmia detection algorithms. The recordings were collected

using a Del Mar Avionics 445 ECG recorder, with a sampling rate of 360 Hz and 11-bit resolution, utilising modified limb lead II and one of V1, V2, or V5 for two channels. Each record is annotated by experts for beat types, rhythm changes, and noise, offering valuable ground truth for machine learning applications. The dataset includes a mix of normal and arrhythmic conditions and is publicly available on PhysioNet, making it a standard benchmark in cardiac signal analysis studies.

- **Real-Time Hospital Dataset:**

The real-time ECG data used in this study were collected from Bhatkar Hospital, located in Amravati, Maharashtra, during the period between 2023 and 2024. Data acquisition was conducted using a 12-lead ECG machine interfaced with the Simul-G software, enabling digital extraction of ECG signals. The dataset comprises clinical ECG recordings from 400 patients, spanning an age group of 28 to 60 years. Among the participants, 200 were male, and 200 were female, ensuring a balanced gender representation. Each ECG signal corresponds to one of five beat categories relevant to cardiac arrhythmia classification. The distribution includes 20 Normal (N) beats, 80 Supraventricular (S) ectopic beats, 147 Ventricular (V) ectopic beats, 111 Fusion (F) beats, and 42 Unknown (Q) beats. The ECG signals were sampled and pre-processed in digital form as provided by the hospital infrastructure. All recordings reflect real-time physiological data, ensuring high clinical relevance and diagnostic variability.

In Table 1.1, we have a comparative study of different ECG datasets for Arrhythmia Detection.

Table 1.1: Comparative Overview of Public ECG Datasets for Arrhythmia Detection

Dataset Name	Source / Availability	Leads	Sampling Rate	Key Features / Purpose
MIT-BIH Arrhythmia	PhysioNet	2	360 Hz	Gold-standard dataset; beat-level annotations for arrhythmia
PTB Diagnostic ECG	PhysioNet	15	1000 Hz	ECG data with clinical metadata; used for MI and disease detection
Deep-Q Arrhythmia	ACM Digital Library	1	500 Hz	Large-scale, annotated ECGs from 299 patients
INCART 12-lead Arrhythmia	PhysioNet	12	257 Hz	30-minute recordings; detailed beat annotations
CACHET-CADB	Technical University of Denmark	3	250–500 Hz	ECG with contextual data (activity, stress, sleep, etc.)
UCSF LAD Dataset	University of California, SF	Hospital ECG	Not specified	Designed for detecting life-threatening arrhythmia alarms
ECG Heartbeat Categorization	Kaggle	12	360 Hz	For the classification of ECG heartbeat types
ECG Arrhythmia Image	Kaggle	12	Derived	Image dataset created from the MIT-BIH and PTB datasets
Real Time Hospital Dataset	Hospital	12	360 Hz	The ECG signals were sampled and pre-processed in digital form as provided by the hospital infrastructure

Healthcare systems have increasingly adopted advanced computational methods to reduce mortality rates. The conservative rule-based diagnosis model is frequently unsuccessful because it must deal with substantial volumes of diverse data, which

necessitates extensive analysis and medical knowledge to get a diagnosis with sufficient precision.

Arrhythmia detection requires computation to automate and improve the precision and effectiveness of ECG analysis, which is difficult and time-consuming for humans, particularly when examining lengthy recordings.

Challenges of Manual ECG Analysis:

- **Time-Consuming:** Analysing ECGs, especially long-term recordings, can be very time-consuming for a human.
- **Subjectivity and Error:** Human interpretation can be subjective and prone to errors, especially during fatigue.
- **Limited Sensitivity:** Traditional ECG analysis may not capture sporadic or transient arrhythmias.

Benefits of Computational Methods:

- **Automation:** Computational techniques, like ML and DL, can automate the process of ECG analysis, making it faster and more efficient.
- **Improved Accuracy:** Algorithms can be trained to recognise subtle patterns and features in ECG signals that humans may miss, leading to more accurate diagnoses.
- **Early Detection:** Computational methods can help in the early detection of arrhythmias, which is crucial for timely intervention and treatment.
- **Objectivity:** Algorithms can provide objective and consistent results, reducing the risk of human error.

- Scalability: Computational methods can be applied to large datasets of ECG recordings, enabling the development of more robust and accurate models

This issue will worsen particularly in developing nations where there is a shortage of medical professionals and clinical supplies. This motivates the requirement for a reliable, automatic, and low-cost system for monitoring and diagnosis [21]. Traditionally, automatic monitoring procedures for health conditions are Computer-Aided Diagnosis (CAD)-based and rely on the analysis of physiological signals to monitor and evaluate the functionality of the corresponding organ. CAD systems provide portable, user-friendly solutions that help keep patients informed about their condition.

In this planned system, one must be able to predict heart disease with additional accuracy and precision. Automation in the medical field spans multiple applications, from treatment identification to compensating for shortages in healthcare services and physician availability. In previous systems, rule-based systems were used early on. However, traditional techniques have proven neither cost-effective nor sufficiently accurate for individualised prediction. Machine Learning (ML) comprises a set of computational techniques that enable systems to learn patterns from data and make predictions or decisions without being explicitly programmed [22–26].

Apart from this, EHRs (Electronic Health Records) are used to record results to improve accuracy across a wide selection of medical tasks. Medical procedures, combined with machine learning, support data-driven prediction, thereby improving the system's overall predictive performance. Hence, the proposed research focuses on deep learning (DL) methods. Deep learning employs neural

networks; a subset of ML techniques composed of multiple layers that extract and represent data at increasing levels of abstraction [27]. The two primary types of automatic categorisation technologies are now deep learning-based techniques and computer signal processing-based techniques. Artificial neural networks (ANNs), frequency analysis, decision trees, k-nearest neighbours, support vector machines, and others make up the first category of automated ECG analysis techniques. Many researchers are using DL for the detection and classification of ECG signals due to the advancement of DL in the computer field [28-30].

1.1.2 Arrhythmia classification challenges

The following succinctly describes the primary difficulties that computer-aided diagnosis systems face while classifying arrhythmias.

1. The ECG signal-capturing period does not show the arrhythmia's symptoms.
2. Age, gender, physical condition, and lifestyle are some of the variables that affect an ECG signal's properties, which vary from one to another and include its period and amplitude. It is difficult to find a generic framework and associated standards that operate for the broader population.
3. Due to physical states like walking, jogging, and sleeping, the ECG signal morphology is frequently not stationary, even for a single test subject.
4. A significant amount of data must be considered for the processing of ECG signals. As a result, the likelihood of receiving a mistaken diagnosis of arrhythmia is increased.
5. The recorded ECG signal exhibits morphological changes and inconsistencies due to noise, artifacts, and interference.

Additionally, regarding ECG analysis, the following questions should be

considered during the research.

Why it's important to keep an eye on your ECG: An ECG test tracks the electrical activity of your heart and shows a moving pattern of peaks and dips. It gauges how much electricity flows through your heart. Although each person's ECG trace is different, some patterns can be used to identify different heart issues, including arrhythmias. Now, what is seen on an ECG? An ECG, in short, tells you whether your heart is functioning normally or if there is a problem with it, and what that issue is.

What are the benefits of getting an ECG? - Numerous heart issues can be screened for and diagnosed with the use of an ECG test. It's the most used method for monitoring cardiac conditions or determining whether your heart is healthy. An ECG scan or long-term monitoring may be beneficial if you have heart disease in your family, are exhibiting symptoms of heart issues, or lead a lifestyle that compromises your health.

Importance of ECG Signals: ECGs help doctors to identify a remarkably fast heart rate (tachycardia) or a remarkably slow heart rate (bradycardia). The heart rhythm of the ECG shows irregularities (arrhythmias), occurs when any part of the heart's electrical system malfunctions.

What is the need for ambulatory care? Medical services accomplished on an outpatient basis, without admission to a hospital or other facility (MedPAC) is known as Ambulatory care. It is provided in surroundings such as Offices of physicians and other health care professionals, hospital outpatient departments, speciality clinics, ambulatory surgical centres, or centres, dialysis or infusion centres, and urgent care clinics. Hence, to get accurate and fast results, it is

necessary to use computational methods. Figure 1.3 shows the overview of traditional computational methods and DL methods for the analysis of ECG.

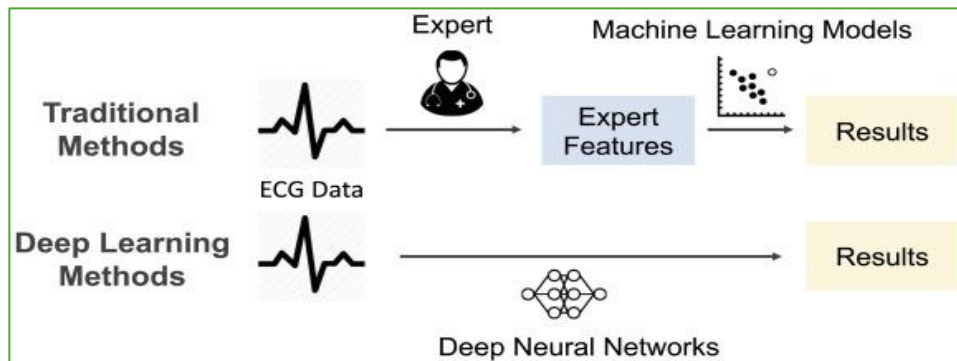


Figure 1.3: Comparisons Between Computational Methods and DL Methods

Hence, it is primarily necessary to evaluate different methods used previously for the prediction of heart arrhythmia identification of the research gaps as technical, physiological and instrumental gaps. Consequently, the proposed research life cycle needs to be developed to achieve superior results to boost the applicability and usability of the proposed model.

Aside from the primary literature review presented in Chapters 2 and 3 during the proposed study, we considered the following elements intended for the secondary literature review (included in Chapter 3):

- 1) Which techniques are performing well compared to older research?
- 2) What problems are handled by existing research?
- 3) What are the challenges during the real-time patient study?
- 4) How proposed algorithm better than existing techniques?
- 5) How proposed research beneficial for healthcare professionals?
- 6) Which parameters are important for the classification of heart arrhythmia conditions?

1.2. Problem Statement

Although numerous machine learning and deep learning techniques have been proposed for ECG-based arrhythmia classification, several technical challenges remain unresolved. Existing ECG denoising methods are generally designed to suppress only specific types of noise, often resulting in distortion of clinically significant morphological characteristics that are essential for accurate diagnosis. Furthermore, many classification approaches rely on handcrafted feature engineering or treat signal denoising and classification as independent processes, limiting their robustness, increasing computational complexity, and reducing their adaptability to noisy real-world ECG signals.

In recent years, deep learning has enabled automatic feature extraction; however, conventional convolutional and recurrent neural network models primarily focus on local or sequential patterns and often fail to effectively capture the long-range temporal dependencies, and global contextual relationships present in ECG signals. This limitation can adversely affect the discrimination of subtle morphological variations among different arrhythmia classes, particularly under severe noise conditions. The application of a Self-Attention-Based Autoencoder (SABAE) offers a promising solution by simultaneously performing adaptive feature representation and global contextual learning. The self-attention mechanism enables the model to identify and assign greater importance to diagnostically relevant regions of the ECG signal while suppressing redundant or less informative features. In addition, the autoencoder architecture learns compact and discriminative latent representations without requiring manual feature extraction, thereby improving classification robustness, reducing feature redundancy, and enhancing the model's ability to generalize across diverse ECG patterns. Moreover, many existing methods are evaluated exclusively on benchmark

datasets, demonstrating limited generalizability to real-time clinical ECG recordings acquired under varying acquisition conditions. Therefore, there is a need for an integrated framework that combines adaptive ECG denoising with intelligent deep feature learning to achieve accurate multiclass arrhythmia classification while maintaining computational efficiency, robustness, and clinical applicability.

To address these challenges, this research proposes an integrated framework consisting of a Tuned Kalman Filter (TKF) for adaptive ECG preprocessing and noise suppression, followed by a Self-Attention-Based Autoencoder (SABAE) for automatic deep feature extraction and multiclass arrhythmia classification. By leveraging the global dependency modeling capability of self-attention and the representation learning strength of autoencoders, the proposed framework aims to preserve clinically important ECG morphology, improve classification accuracy under severe noise conditions, enhance generalization across both benchmark and real-time ECG datasets, and provide a reliable and computationally efficient solution for intelligent arrhythmia diagnosis.

1.3. ECG-based arrhythmia identification and classification

ECG-based arrhythmia identification and classification involve a hierarchical process: ECG signal preprocessing, heartbeat segmentation, feature extraction, and finally, classification using ML or DL models. Figure 1.4 shows the hierarchical process of ECG-based arrhythmia identification and classification.

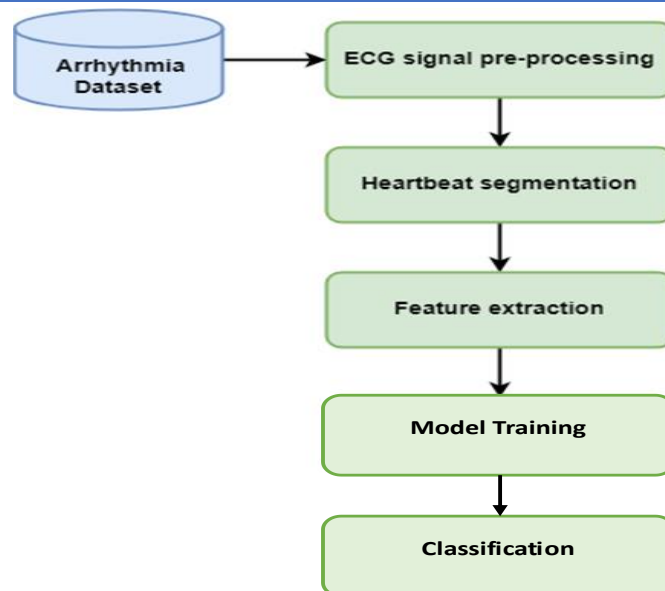


Figure 1.4: Hierarchical Process Of ECG-Based Arrhythmia Identification And Classification

As shown in Figure 1.4, each process has been executed during the proposed research as:

1. ECG Signal Pre-processing:

This stage aims to clean the raw ECG signal by removing noise and artifacts that can interfere with accurate analysis. Common techniques include filtering (band-pass filtering to remove unwanted frequencies), baseline wander removal, and artifact suppression. For the demonstration of ECG signal preprocessing, a Tuned Kalman filter is developed during the proposed research.

2. Heartbeat Segmentation:

To isolate individual heartbeats (QRS complexes) from the ECG signal for analysis is required. Algorithms identify peaks of the QRS complex, which represent

ventricular depolarisation, to segment the ECG signal into individual heartbeat intervals.

3. Feature Extraction:

To extract relevant features from the segmented heartbeats that can distinguish between different arrhythmia types. These features can include morphological characteristics (e.g., QRS duration, RR interval, P-wave morphology), time-frequency domain features (e.g., spectrograms), and other statistical measures.

4. Classification:

To classify segmented heartbeats into diverse arrhythmia categories based on extracted features. ML algorithms (Support Vector Machines (SVM), Random Forests (RF), Logistic Regression (LR)) or DL models (Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN)) are used for classification. The proposed method is developed for the enhancement of accuracy, recall, and F1-score, and a confusion matrix is generated.

1.4 Scope of the work

Finally, employed DL techniques to create the suggested system from start to finish. The MIT-BIH Arrhythmia Dataset, the most reputable and frequently suggested dataset utilised in current research, is used to test the suggested system. Chapter 6 of this thesis discusses how this makes a performance comparison more effective. So, performance comparison is done more efficiently, which is discussed in Chapter 7 of this thesis. The real-time ECG report testing is done with a newly developed analogue-to-digital ECG analysis, which gives the peaks of ECG signals for the analysis of the state of arrhythmia.

1.5 Objectives

The primary literature review states that the proposed study aims to cover a wide range of DL methods in arrhythmia classification. Their focus is on heart arrhythmia(s), so the objective is broadly classified as:

1) To study and analyse the existing techniques to classify heart arrhythmia:

→ In this objective, we targeted LR, KNN, SVM, DT Classifier, RF, and XGBoost to identify the methodological and performance differences.

2) Collect and pre-process the patients' ECG data on standard parameters:

→ To achieve this objective, we resolved “Why the Kalman Filter is more efficient than the notch Filter and why we are using it?” and proposed a tuned Kalman filter for better handling of the PLI noise level.

3) To develop a novel deep-learning algorithm to predict heart arrhythmia:

To achieve this goal, a self-attention-based AI Auto Encoder model is created and contrasted with current algorithms with accuracy, recall, and precision metrics. The objective is to increase the model's predictive accuracy for cardiovascular illnesses.

4) To compare existing classification methods with the proposed work:

→ We accomplished this goal by comparing the outcomes of our state-of-the-art algorithm execution with those of existing algorithms. We also conducted a post-feasibility analysis of the proposed system, including an analysis of traditional methods and their impact on patients with cardiac arrhythmia.

1.6 Novelty of the Proposed Research:

The originality of the proposed research is demonstrated through the following technical contributions.

Contribution 1

A Tuned Kalman Filter (TKF) is proposed for the adaptive suppression of power-line interference and ECG noise while effectively preserving the critical morphological characteristics of ECG signals. Unlike conventional Kalman filters and fixed-parameter filtering techniques, the proposed TKF is optimised for arrhythmia detection and analysis, thereby enhancing noise reduction without compromising diagnostically significant features. The proposed approach was evaluated under a challenging noise condition with a signal-to-noise ratio (SNR) of -30 dB, demonstrating its robustness and effectiveness in accurately denoising highly corrupted ECG signals.

Contribution 2

A Self-Attention Autoencoder-based deep learning architecture is developed for automatic feature extraction and multi-class arrhythmia classification. The attention mechanism enables the model to learn both local waveform characteristics and long-range temporal dependencies without relying on handcrafted features.

Contribution 3

Unlike existing studies that separately perform signal denoising and classification, the proposed work integrates ECG preprocessing, heartbeat segmentation, feature learning, and classification into a unified framework.

Contribution 4

The proposed framework is validated using both the MIT-BIH benchmark dataset and real-time ECG recordings collected from hospital patients, demonstrating improved practical applicability.

Contribution 5

The proposed framework improves classification performance while maintaining computational efficiency, making it suitable for future wearable and real-time ECG monitoring systems.

Table 1.2 Proposed Research Novelty Work

Existing Research	Proposed Research
Standard Kalman Filter	Tuned Kalman Filter
CNN	Self-Attention Autoencoder
Only preprocessing	Integrated preprocessing + classification
Benchmark dataset only	Benchmark + Real Hospital Dataset
Manual feature dependency	Automatic feature learning
Single-stage improvement	End-to-end framework

1.7 Hypotheses Formulation

For the post-feasibility analysis of the proposed research objectives, the following hypotheses were formulated, and hypothesis testing was conducted and presented in Chapter 5 of this thesis.

Hypothesis I:

H₀: Cardiac arrhythmia does not contribute to cardiac arrest or any other heart disease.

H₁: Cardiac arrhythmia contributes to cardiac arrest or any other heart disease.

Hypothesis II:

H₀: Traditional ECG report analysis is an efficient method for the identification of the state of cardiac arrhythmia.

H₁: Traditional ECG report analysis is not an efficient method for the identification of the state of cardiac arrhythmia.

Hypothesis III:

H₀: Manual analysis of real-time patient ECG report data is trustworthy and without human error.

H₁: Manual analysis of real-time patient ECG report data is not trustworthy and may contain human error.

Hypothesis IV:

H₀: When it comes to classifying cardiac arrhythmias, the suggested DL method is not particularly effective.

H₁: When it comes to classifying cardiac arrhythmias, the suggested DL method is more effective.

Hypothesis V:

H₀: The suggested Tuned Kalman filter is ineffective at managing PLI and lowering the ECG signals' noise level.

H₁: The proposed Tuned Kalman filter is more efficient in handling PLI and reducing the noise level of ECG signals.

Hypothesis VI:

H₀: There is no need for classification of ECG for a single heartbeat to identify a risky heartbeat.

H₁: There is a need for classification of ECG for a single heartbeat to identify a risky heartbeat.

Hypothesis VII:

H₀: The performance of unconventional classification methods is not necessary to evaluate the proposed system.

H₁: The performance of the state-of-the-art classification methods is necessary to evaluate the proposed system.

Hypothesis – VIII:

H₀: The proposed deep learning framework cannot reliably classify ECG signals recorded before and after the OM chanting intervention.

H₁: The proposed deep learning framework can reliably classify ECG signals recorded before and after the OM chanting intervention.

Hypothesis IX:

H₀: As a future scope, the proposed system cannot be implemented as a component of a wearable IoT device for patients with heart diseases.

H₁: As a future scope, the proposed system can be implemented as a component of wearable IoT devices for patients with heart diseases.

1.8 Research Methodology

We applied experimental research methodology along with quantitative and exploratory research methodology. As the proposed system focused on the classification of cardiac arrhythmia, the execution of the proposed study is broadly organised as:

- i) Existing system study.
- ii) Identification of technical research gaps.
- iii) Designing and developing the proposed Tuned Kalman filter.
- iv) Development of the proposed deep learning algorithm
- v) Development of a real-time ECG analysis tool
- vi) Post-research feasibility analysis.

The overall research life cycle methodology is depicted in Figure 1.5.

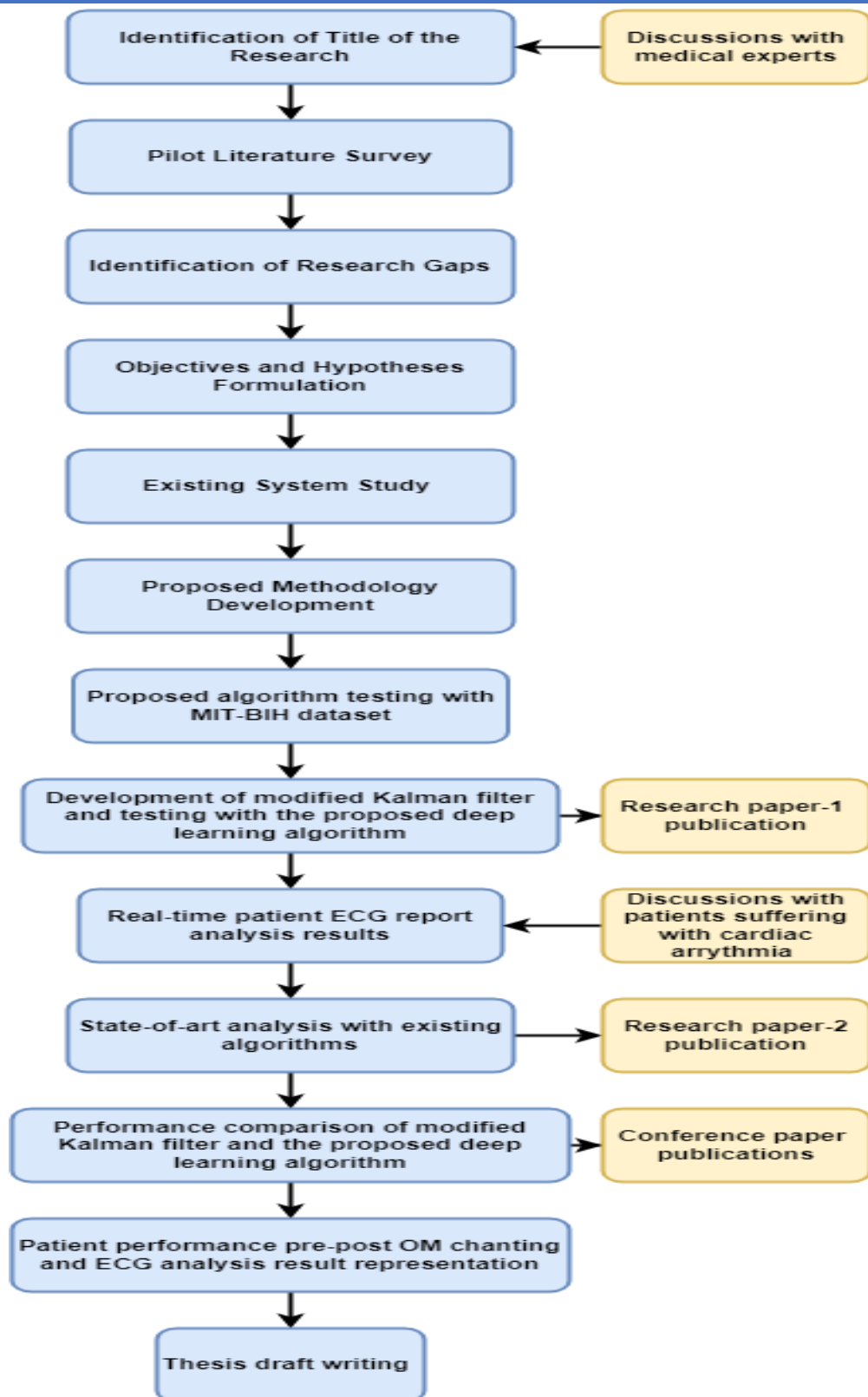


Figure 1.5: Proposed Research Life Cycle Methodology

Based on the research life cycle, we executed the proposed research. Further, for a real-time patient ECG data study, we calculated the sample size for the real-time patient study using the Yamane formula, and participants were shortlisted from Amravati City, Maharashtra, India:

$$n_s = N_p / (1 + (N_p \times e_v \times e_v))$$

n_s = Sample size for N_p population

N_p = Population

e_v = Variance of sample (0.05)

$$n_s = 808,263 / (1 + (808,263 * 0.05 * 0.05))$$

$$n_s = 399.80$$

As participants can't be odd figures, we rounded up to

$$n_s = 400$$

According to “World Population Review”, the total population of Amravati City is 808,263 as of by the year 2024 (<https://worldpopulationreview.com/cities/india/amravati>). Hence, for reliability testing, this research considered 10% of the calculated sample size as 40 patient data. Thus, 40 ECG reports were collected with the permission of the doctor from Amravati City, Maharashtra, India.

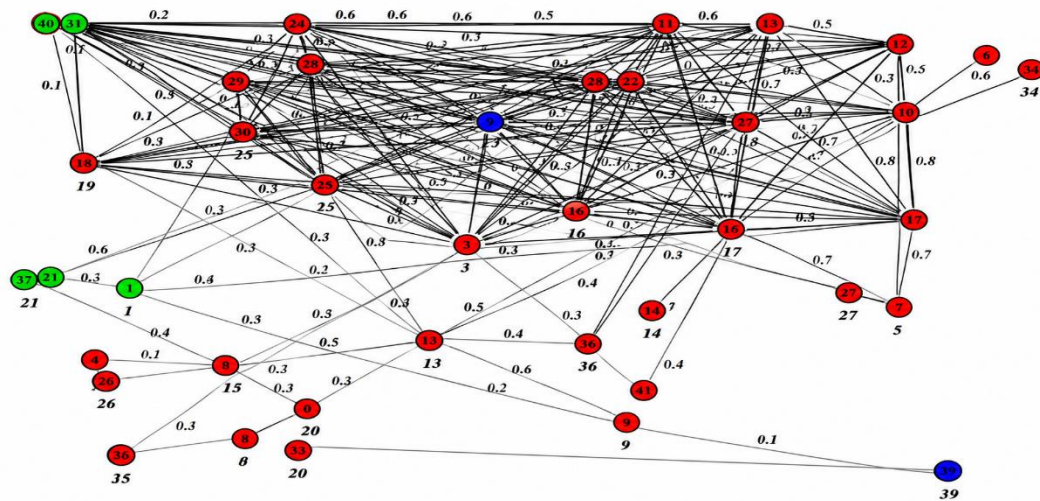


Figure 1.6: Reliability Of Participants' Graph of The Proposed Study

The participants' cardiac arrhythmia conditions are shown in Figure 1.6, and the red dots show the number of patients suffering from cardiac arrhythmia for more than 3 years, the blue dots show patients suffering from cardiac arrhythmia for more than 3 years, and the green dots show patients suffering from cardiac arrhythmia in the past 1 year. The real-time ECG study intends to validate the proposed study and to utilise these participants to verify the pre-and post- “OM chanting” impact.

For testing purposes, we scanned and stored the data, which was further tested with an analogue-to-digital transformation and identification of the QRS complex. The same data and participants were considered for the “OM chanting” session, which will be discussed later in this thesis.

1.9 Research Limitations

- 1) The proposed system is tested on the MIT-BIH Cardiac Arrhythmia dataset and a real-time patient dataset.
- 2) The proposed framework was implemented and evaluated on a single-server CPU-based computing platform. Performance optimization and computational speedup using GPU-based hardware were not investigated and may be considered in future work.
- 3) As real-time patient ECG data is collected with the permission of doctors,
- 4) The OM chanting dataset was collected from participants within Amravati City, Maharashtra, India. Therefore, the findings may have limited generalizability to populations with different demographic and geographical characteristics. Once the chanting is completed, we have taken the features of Heart Rate (HR), PR Interval, QRS Duration, and RR Interval.

1.10 Thesis Organisation

This thesis is structured in alignment with the proposed research framework to ensure a logical flow of information and systematic exploration of the problem domain:

- **Chapter 1: Introduction** - Provides an overview of cardiovascular diseases, the need for advanced diagnostic systems, and outlines the motivation, objectives, and scope of the research.
- **Chapter 2: Literature Review** - Presents a critical review of existing studies, techniques, and methodologies relevant to cardiac arrhythmia detection, highlighting current challenges and research gaps.

- **Chapter 3: Arrhythmia Classification Methods Based on ML/DL Techniques**

This chapter describes the classification-based ML and DL techniques for arrhythmia detection using ECG signals.

- **Chapter 4: Research Methodology** - Describes the proposed deep learning-based approach, data preprocessing, model design, and experimental setup for ECG signal classification.

- **Chapter 5: Implementation and Experimental Setup** – Translates the theoretical architecture into a practical executable pipeline that supports real-time and high-accuracy classification of the ECG Signal.

- **Chapter 6: Results and Performance Evaluation**- Analysis of the experimental results obtained from implementing the proposed arrhythmia classification framework.

- **Chapter 7: Comparative Analysis and Discussion** – Comparative Analysis of the proposed arrhythmia classification framework with existing state-of-the-art methods, including accuracy, noise, robustness, efficiency, real time applicability.

- **Chapter 8: Feasibility Study and Development Assessment:** Finding the feasibility of the classification of cardio arrhythmias, we used hypothesis formulation.

- **Chapter 9: Conclusions, Recommendations, and Future Scope** - Summarises key findings, offers conclusions based on research outcomes, and suggests potential directions for future work in this domain.

1.11 Chapter Summary

CVD remains a leading cause of death globally, with a rising mortality rate in India due to non-communicable factors like hypertension, diabetes, and high cholesterol. Traditional diagnostic approaches often fall short when handling complex, heterogeneous health data. This chapter emphasises how computer-aided diagnosis tools and DL approaches are becoming increasingly relevant, especially for the identification and categorisation of cardiac arrhythmias. It outlines the limitations of conventional ECG analysis and introduces heartbeat classification strategies such as inter-patient, intra-patient, and patient-specific models. The MIT-BIH arrhythmia dataset is identified as suitable for the proposed methodology, which aims to enhance prediction accuracy through deep learning. Chapter 1 concludes with an overview of the research framework and the motivation behind the study.

CHAPTER 2

BROAD REVIEW OF ARRHYTHMIA CLASSIFICATION METHODS

2.1 Primary Literature Review

This chapter offers a comprehensive literature review that starts with a broad overview of existing denoising and classification methods for ECG signals and then moves toward more specialised techniques closely aligned with the proposed methodology. The discussion is organised into two sections: ECG denoising techniques and arrhythmia classification techniques. Each theme is further divided based on methodological approaches, specifically ML, DL, and Soft Computing.

2.1.1 Denoising Techniques for ECG Signal

Noise and artifacts, baseline wander, muscle noise, and powerline interference can significantly compromise the accuracy of ECG signal interpretation. Several approaches have been proposed for effective noise removal.

2.1.2 ML-Based Denoising Methods

Qian et al. [27] employed traditional signal processing methods like FIR, IIR filtering, Variational Mode Decomposition (VMD), Empirical Mode Decomposition (EMD), and recursive filtering for noise attenuation. However, these methods were limited in handling PLI effectively, warranting the development of specialised PLI reduction techniques.

Table 2.0: Authors' Performance Metrics

Qian et al. (2019)	Your Proposed Work
Local Means denoising	Tuned Kalman Filter
Compared with NLM	Compared with conventional denoising methods
21% higher SNR improvement than NLM	Validated under -30 dB SNR
About 100× lower computational cost	Morphology-preserving adaptive filtering for arrhythmia classification
Focused on denoising	Denoising + Self-Attention Autoencoder-based multiclass arrhythmia classification

Additionally, Least Mean Square (LMS) filters, Kalman filters, and Band-stop filters (IIR/FIR/DFT-based) have been compared for removing power-line interference (PLI), with FIR and IIR showing better signal-to-noise ratio (SNR) performance but limited efficacy against Gaussian noise [30].

Gaamouri et al. [31] advanced the field by proposing a dual Unscented Kalman Filter (UKF) integrated with a Multilayer Perceptron (MLP) to adaptively filter out Gaussian and muscle artifacts. The Kalman filtering-based approach showed potential, although it still left room for enhancement in model generalisation and signal recovery. This paper reports quantitative performance values, primarily using Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR). The experiments were conducted with white Gaussian noise, pink Gaussian noise (input SNR = 5 dB), and muscle artifact noise (input SNR = 12 dB and 18 dB). It does not evaluate performance at -30 dB SNR.

Table 2.1: Authors' Performance Metrics

Method	Noise Type	MSE	PSNR (dB)
Band-Pass Filter (BF)	White noise	0.122	45.16
Median Filter (MF)	White noise	0.012	55.23
Wavelet Filter (WF)	White noise	0.012	55.23
Proposed UKF-MLP	White noise	0.002	63.01
Band-Pass Filter (BF)	Pink noise	0.175	43.59
Median Filter (MF)	Pink noise	0.134	44.75
Wavelet Filter (WF)	Pink noise	0.113	45.49
Proposed UKF-MLP	Pink noise	0.016	53.98

Table 2.2 Results for muscle artifact noise

Frequency of SNR	MSE (UKF)	PSNR (UKF)
12 dB	1.371	34.65 dB
18 dB	0.983	36.09 dB

Mukhopadhyay and Krishnan [32] proposed a model-free ECG denoising technique based on Singular Spectrum Analysis (SSA) to overcome the limitations of conventional model-dependent and sampling-rate-dependent methods. The proposed approach was evaluated using 695 ECG recordings collected from five publicly available databases and demonstrated superior denoising performance compared with existing state-of-the-art techniques. The denoised ECG signals achieved a Mean Opinion Score (MOS) based on expert subjective evaluation while effectively suppressing white Gaussian noise, random noise, baseline wander, power-line interference, and instrumentation noise without compromising clinically significant ECG morphology. However, the study did not investigate the algorithm under extremely low signal-to-noise ratio conditions, leaving its robustness in highly corrupted ECG environments unexplored.

Traditional filtering techniques such as Finite Impulse Response (FIR), Infinite Impulse Response (IIR), Least Mean Square (LMS), and Kalman filters have been widely employed to boost SNR in ECG signals. To address non-linear and time-varying noise characteristics, a Dual Unscented Kalman Filter integrated with a Multilayer Perceptron (UKF-MLP) has been proposed for adaptive artifact removal. Furthermore, multi-stage denoising pipelines combining VMD

Marginalised Particle-Extended Kalman Filtering (MP-EKF) have shown promise in preserving morphological integrity while significantly improving signal recovery.

2.1.3 DL-Based Denoising Methods

The ability of DL architecture-based advanced denoising techniques, including Stacked Denoising Autoencoders (SDAEs), to learn hierarchical representations has made them increasingly popular. Xia et al. [17] proposed an automatic cardiac arrhythmia classification system based on a Stacked Denoising Autoencoder (SDAE) integrated with Softmax regression and active learning for wearable ECG analysis. The model was evaluated on the MIT-BIH Arrhythmia Database and a wearable ECG dataset following the AAMI classification standard. Using the Modified Breaking-Ties (MBT) active learning strategy, the proposed framework achieved an accuracy of 99.8%, sensitivity of 94.3%, specificity of 99.9%, and positive predictive value (PPV) of 95.3% for supraventricular ectopic beat (SVEB) classification. For ventricular ectopic beat (VEB) classification, the method achieved 99.8% accuracy, 98.4% sensitivity, 99.9% specificity, and 99.8% PPV. Although the proposed SDAE-based framework demonstrated excellent classification performance, it primarily focused on ECG

classification and did not investigate robust ECG denoising under extremely low signal-to-noise ratio conditions, such as -30 dB SNR, which remains an important challenge for reliable arrhythmia diagnosis in highly noisy environments.

Dual Unscented Kalman Filters (UKF) integrated with Multilayer Perceptron (MLP) networks have also been proposed to suppress white, coloured Gaussian, and non-stationary noise. MLP served as the nonlinear model, while the UKF estimated both clean signals and MLP weights [31].

DL techniques have demonstrated enhanced adaptability in noisy environments. Singh and Pradhan [33] developed an end-to-end Generative Adversarial Network (GAN)-based model trained on paired clean and noisy ECG signals from the MIT-BIH dataset. This approach bypassed hand-crafted feature dependency and significantly improved noise reduction. This approach showed superior performance over traditional filtering techniques.

Furthermore, mobile and cloud-based systems like QardioCore with QardioMD offer three-lead ECG streaming to cloud platforms with automated noise filtering and arrhythmia recognition. Automated detection of QRS morphology, P-waves, and ST segments supports high-accuracy arrhythmia detection. Preliminary evaluations show diagnostic performance comparable to that of Holter monitors.[125]

Recent advancements in DL-based denoising have introduced SDAEs embedded in wearable ECG monitoring systems for robust signal reconstruction.[126] .The authors mainly evaluated the SVEB and VEB classes according to the AAMI standard.

Table 2.3: Authors' Performance Metrics

Metric	SVEB	VEB
Accuracy	94.4%	94.9%
Sensitivity	17.6%	83.3%
Specificity	93.7%	93.9%
Positive Predictive Value (PPV)	51.6%	57.0%

GANs trained on paired clean and noisy ECG signals offer end-to-end denoising with high fidelity.[33] Additionally, emerging real-time platforms, such as QardioCore integrated with the cloud-based QardioMD system, enable continuous, mobile-based ECG monitoring and artifact removal, thereby enhancing the practicality of ambulatory cardiac care [125].

2.1.4 Soft Computing Approaches for Noise Reduction

Soft computing methods such as fuzzy logic and evolutionary algorithms have also been explored for their adaptability in handling uncertainty and variability in real-world ECG recordings. Soft computing methods have gained attention for their ability to manage uncertainty and nonlinearity in physiological signals.

A major diagnostic gap was left when Anwar et al. [18] used Discrete Wavelet Transform (DWT) to extract morphological aspects of individual heartbeats but did not apply their method to high-risk beat prediction. Although the proposed hybrid feature approach demonstrated excellent classification performance, it relied on handcrafted features and did not incorporate adaptive ECG denoising or end-to-end deep feature learning, both of which are addressed in the proposed research. Performance values of Anwar et al are shown in the table below.

Table 2.4: Authors' Performance Metrics

Parameter	Value
Dataset	MIT-BIH Arrhythmia Database + MIT-BIH Supraventricular Arrhythmia Database
Total heartbeats	35,875
Training strategy	Three-fold cross-validation
Number of classes	18 (class-oriented) and 5 (subject-oriented, ANSI/AAMI)
Feature dimension	17 (12 DWT-ICA coefficients + 4 RR interval features + 1 TEO feature)

Wavelet Transform (WT) is widely used for feature extraction and denoising due to its capability for time-frequency localisation. Figure 2.1 presents a typical wavelet transform block diagram [25].

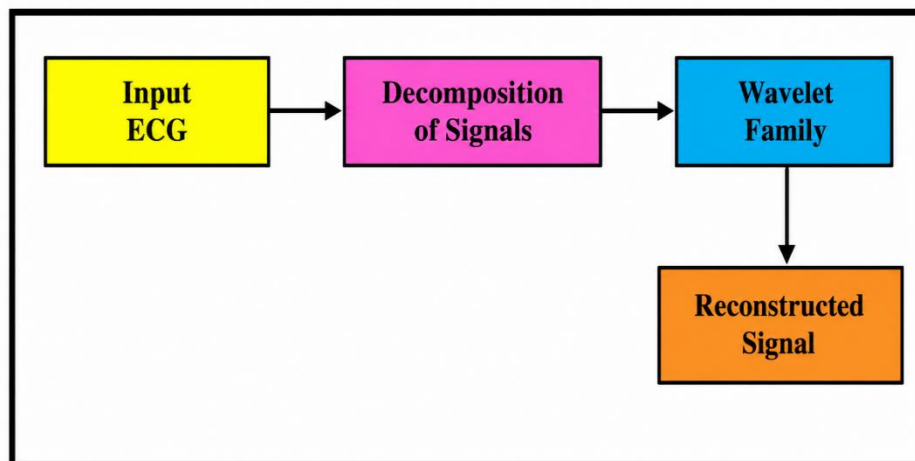


Figure 2.1: Block Diagram of The Plain Wavelet Transform [130].

Soft computing models offer adaptability, making them suitable for handling uncertain and diverse noise patterns. WT remains a widely used approach due to its time-frequency localisation ability. However, WT lacks adaptability for handling diverse noise types. A more flexible method, the Empirical Wavelet Transform (EWT) combined with Wavelet Thresholding, was developed for non-contact ECG signals. The process involves spectrum preprocessing, EWT

decomposition, and reconstruction. This method effectively retains QRS complexes and improves SNR. Spectrum preprocessing, segmentation, EWT decomposition, wavelet threshold denoising, and reconstruction are the five steps of a fusion denoising technique that combines EWT and WT. It shows improved QRS preservation and SNR when applied to real ECGs from non-contact devices [26].

Table 2.5: Authors' Performance Metrics

Parameter (Xu, Xiaowen)	Value
Dataset	MIT-BIH Arrhythmia Database + MIT-BIH Noise Stress Test Database
Noise Type	Motion artifact
Number of ECG records	10
Input SNR	0 dB
Compared Methods	DWT, EMD, EWT, Proposed EWT-WT
Evaluation Metrics	Correlation Coefficient (Corr), MSE, PRD, SNR Improvement

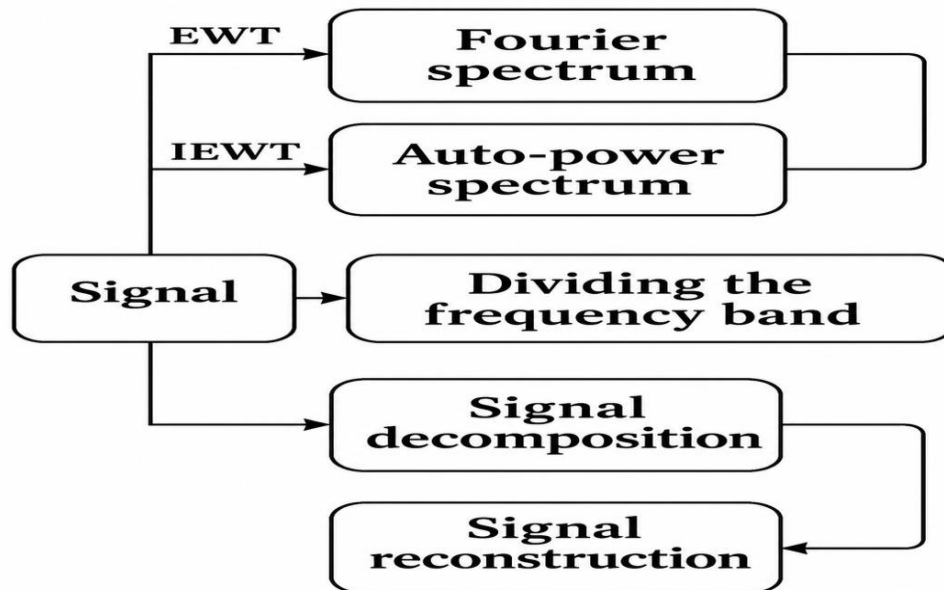


Figure 2.2: Representation of empirical wavelet transforms (EWT) [132]

Refer to Figure 2.3 for EWT architecture. Other common denoising methods include FIR and IIR filters, EMD, VMD, Non-Local Means (NLM), recursive filtering, and inverse Bayesian techniques [27].

Hao et al. [28] introduced MP-EKF for ECG denoising, achieving favourable results in general noise reduction. Despite strong denoising performance under normal conditions, MP-EKF underperforms in scenarios involving abrupt amplitude changes from abnormal heartbeats. While traditional techniques like the Fourier Transform (FT) and filter-based methods provide basic noise suppression, they are constrained by a lack of adaptability and real-time analysis capability. FT analyses the signal, making it unsuitable for local transient noise, whereas some filter methods degrade clinically relevant components of the ECG.

Table 2.6: Authors' Performance Metrics

Performance Metric of Hao al.	Reported Value
Maximum SNR Improvement	21.54 dB
Mean Squared Error (MSE)	< 0.0401
Datasets	MIT-BIH Arrhythmia Database and St. Petersburg 12-lead Arrhythmia Database
Noise Types	White Gaussian Noise and Muscle Artefact Noise
Compared Methods	Wavelet Transform (WT), Empirical Mode Decomposition (EMD), Variational Mode Decomposition (VMD), Non-Local Means (NLM), and other state-of-the-art denoising methods
Major Finding	Better preservation of abnormal beats and ECG morphology under complex noise conditions

Neural network-based techniques like Denoising Autoencoders (DAEs), Wavelet Neural Networks (WNN), and Functional Link Neural Networks (FLNN) were investigated by Wang et al. [29]. While DAEs showed improved performance, FLNN and WNN only target specific noise types, limiting their robustness.

However, the experiments were conducted for input SNRs ranging from 0 dB to 5 dB, and the robustness of the method under extremely low SNR conditions was not investigated.

Manju and Sneha [30] compared FIR and IIR filters against Kalman and Wavelet-based techniques, noting superior SNR values. Yet, they also highlighted the filters' limitations in removing Gaussian noise, suggesting the need for more intelligent adaptive filtering designs.

WT, particularly DWT, is widely used for QRS complex detection and signal decomposition. However, adaptability remains a limitation. EWT-WT denoising workflows for motion artifact correction in non-contact monitoring. Wavelet Transform (WT), WNNs, and FLNNs for adaptive noise reduction, albeit with limited generalizability. Empirical Mode Decomposition (EMD), Bayesian thresholding, and other adaptive signal decomposition techniques.[28-31-38]

Although the Fourier Transform facilitates effective frequency domain analysis, it cannot perform localised and real-time signal interpretation. While useful in noise suppression, traditional filtering methods often risk attenuating diagnostically significant components of the ECG signal [27]. Consequently, advanced soft computing and DL approaches have emerged as more adaptive and robust frameworks for ECG denoising, offering improved noise resilience while preserving critical morphological features [31]

2.2 Classification Techniques for Arrhythmia

Classifying arrhythmias accurately after denoising is still a crucial effort. The methods utilised for ECG-based arrhythmia identification are reviewed in this section, ranging from sophisticated DL models to classical ML.

2.2.1 ML Approaches

Sannino et al. [16] utilised the WEKA platform for ECG signal classification, suggesting that future improvements should focus on automating feature extraction and classification through DL. For the classification of arrhythmias, ML methods like SVM, RF, JRip, and DT are widely utilised. A key factor in increasing classification accuracy is featuring selection.

Table 2.7: Authors' Performance Metrics of Methods

Dataset	Accuracy	Sensitivity	Specificity
Training Set	100.00%	100.00%	100.00%
Testing Set	99.09%	98.55%	99.52%
Whole Dataset	99.68%	99.48%	99.83%

The study performed binary classification (normal vs. abnormal) rather than multiclass arrhythmia classification. It did not include an adaptive ECG denoising stage before classification. Evaluation was limited to the MIT-BIH Arrhythmia Database. The robustness of the model under extremely noisy conditions was not investigated.

Singh and Singh [22] proposed a machine learning-based framework for cardiac arrhythmia classification using filter-based feature selection techniques on the UCI Cardiac Arrhythmia Dataset. The study evaluated Information Gain, Gain Ratio, and Relief feature selection methods in conjunction with Linear Support Vector

Machine (SVM), Random Forest, and JRip classifiers. The best performance was achieved by the Random Forest classifier using Gain Ratio feature selection with a subset of 30 features, resulting in a classification accuracy of 85.58%. Although the proposed framework demonstrated the effectiveness of feature selection for improving classification performance, it relied on handcrafted clinical features rather than raw ECG waveform analysis and did not incorporate adaptive ECG denoising or deep feature learning for robust arrhythmia detection under noisy conditions.

Alarsan and Younes [23] adopted decision trees and random forests in a big data context for ECG classification using RF and DT, demonstrating the feasibility of real-time, scalable analysis. This work utilised big data frameworks (Hadoop) for large-scale ECG processing and classification. However, a detailed comparison against more recent neural approaches is lacking.

Table 2.8: Authors' Performance Metrics

Classifier (Alarsan and Younes)	Accuracy	Sensitivity	Specificity
Gradient Boosted Tree (GBT)	96.75%	97%	96%
Random Forest (RF)	97.98%	98%	98%

Relied on handcrafted heartbeat features rather than deep feature learning. Did not include an ECG denoising or preprocessing stage. Did not investigate robustness under severe noise conditions. Focused on machine learning classification rather than end-to-end deep learning.

Advances in smartphone-based arrhythmia detection rely on ML-enabled rhythm-strip generation using products like Kardia Mobile and ECG Check, which detect AF using PPG or external metal sensors [127-128]. Time-domain feature

extraction, including QRS duration, RR interval, and segment slopes, was among the earliest methods, implemented even on minicomputer systems as early as the 1980s [129].

Drug-induced arrhythmias, such as torsade de pointes, underscore the need for ECG-based classification linked with pharmacovigilance. Identifying drugs that prolong the QT interval and applying continuous ECG monitoring can mitigate risks. Classifiers can be trained to predict arrhythmogenic potential from drug exposure [39]. Classification models are also crucial for evaluating QoL metrics, as arrhythmia severity and symptom frequency correlate with reduced QoL. Patients with both AF and AFL show less improvement post-ablation, indicating the need for stratified classification approaches [40].

Myocardial fibrosis detection and its relation to arrhythmia substrate, especially in nonischaemic vs ischaemic HF patients, emphasises personalised classification systems based on arrhythmogenic potential. Hypertensive heart disease frequently leads to atrial and ventricular arrhythmias. ML can assist in differentiating arrhythmia ethology due to drug effects, sympathetic overactivation, or structural remodelling [42]. The ASTA questionnaire provides validated PROMs-based classification, enabling symptom and QoL assessment in tachyarrhythmias [43].

Machine learning-based classification of arrhythmias has employed algorithms such as SVM, RF, and JRip, often enhanced through filter-based feature selection techniques to improve diagnostic accuracy. Early models focused on time-domain features, such as QRS complex duration and RR intervals, for reliable arrhythmia typing. More recent approaches have integrated patient-reported outcome measures (PROMs), such as the ASTA questionnaire, to enable symptom-

driven classification strategies. Furthermore, machine learning has demonstrated strong potential in predicting drug-induced arrhythmias and assessing arrhythmic risks in hypertensive patients, offering a personalised and preventive perspective in cardiovascular care.

2.2.2 DL Approaches

In the classification of arrhythmias, DL models, predominantly CNNs and Long Short-Term Memory (LSTM) networks, have shown excellent performance. LSTM networks have been shown to outperform other models in binary classification tasks for ECG arrhythmia, with suggestions to optimise performance further through hyperparameter tuning [18].

Singh et al. [19] proposed a recurrent neural network (RNN)-based framework for automatic ECG arrhythmia classification using Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and conventional RNN architectures. The models were evaluated on the MIT-BIH Arrhythmia Database for binary heartbeat classification. Among the evaluated models, the LSTM achieved the highest classification accuracy of 98.70%, followed by the GRU (98.55%) and the conventional RNN (97.85%), demonstrating the effectiveness of recurrent neural networks in learning temporal dependencies from ECG signals. However, the proposed framework was limited to binary heartbeat classification, lacked an adaptive ECG denoising stage, and did not incorporate attention mechanisms to enhance the discriminative representation of complex arrhythmia patterns.

Hannun et al. [21] proposed a 34-layer Convolutional Neural Network (CNN) for automated arrhythmia detection and classification using single-lead ambulatory ECG recordings. The model was trained and evaluated on a large-scale dataset comprising

91,232 ECG recordings collected from 53,877 patients and classified into 12 cardiac rhythm categories. The proposed CNN achieved an average F1 score of 0.837, surpassing the average cardiologist F1 score of 0.780, thereby demonstrating cardiologist-level diagnostic performance. Furthermore, the model achieved high classification performance for several rhythm classes, including Normal Sinus Rhythm ($F1 = 0.97$) and Atrial Fibrillation ($F1 = 0.96$). Despite its excellent classification capability, the framework was developed using single-lead ambulatory ECG recordings and did not incorporate an explicit ECG denoising stage or an interpretable feature extraction mechanism for preserving clinically significant waveform characteristics.

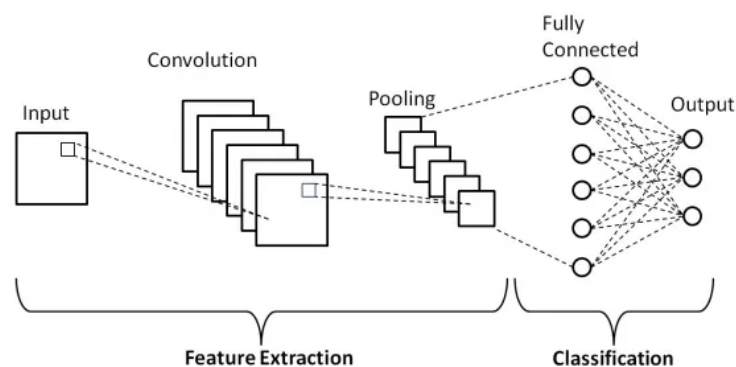


Figure 2.3: Representation of a Deep Convolutional Neural Network [131]

CNNs were suggested as the next step to enhance accuracy and reduce reliance on handcrafted features. These models can capture spatial hierarchies in ECG waveforms. For end-to-end classification, Deep Convolutional Neural Networks (DCNNs) can integrate low, mid, and high-level features thanks to their hierarchical architecture. But traditional ECG detection systems frequently depend on expert interpretation and manually created features, which adds to the computational load [24].

The k-NN classifier has been used to distinguish normal vs abnormal ECG beats based on R-peak detection following VMD and wavelet preprocessing [32]. Wearable smart devices like the Apple Watch and Kardia Mobile use DL for arrhythmia detection, enabling continuous outpatient monitoring despite hardware limitations [34]. QoL-linked classification is essential, especially in asymptomatic AF patients, where clinical risk remains hidden. DL-based screening models show potential to stratify silent AF cases [40].

DL architectures such as LSTM networks and CNNs have been widely adopted for multi-class arrhythmia classification, particularly utilising benchmark datasets like MIT-BIH. These models effectively capture temporal and spatial dependencies within ECG signals, facilitating high-accuracy classification. In parallel, mobile-integrated deep learning tools, such as the Apple Watch and Kardia Mobile, enabled continuous, real-world ECG monitoring and classification, expanding accessibility beyond clinical settings. DCNNs have further advanced the field by offering end-to-end classification of noisy ECG signals, eliminating the need for manual feature engineering. Additionally, quality-of-life (QoL)-driven deep learning models are being developed to improve screening for asymptomatic or atypical presentations of atrial fibrillation (AF), thereby addressing key diagnostic challenges in real-world cardiac care.

2.2.3 Soft Computing Approaches

In addition to ML and DL, soft computing techniques incorporating wavelet transforms and energy operators have been proposed. For example, morphological features derived from Discrete Wavelet Transform (DWT) combined with dynamic

RR interval features (processed using Teager energy operator) have improved classification accuracy, revealing the utility of hybrid time-frequency domain features for detecting quasiperiodic patterns [17].

Marinho et al. [20] proposed a novel ECG feature extraction framework for cardiac arrhythmia classification by integrating Higher-Order Statistics (HOS), Structural Co-occurrence Matrix (SCM), Fourier Transform, and Goertzel Transform with machine learning classifiers, including Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), Bayesian, and Optimum-Path Forest (OPF). The proposed framework was evaluated on the MIT-BIH Arrhythmia Database following the AAMI EC57 standard, where the HOS-based feature extraction achieved the highest classification accuracy of 94.3%. The proposed method was reported to be 1.3% more accurate than the best previously published approach while providing approximately a 2% improvement in confidence level for arrhythmia detection and significantly lower computational time. However, clinical classification underestimates AF burden compared to long-term ECG monitoring. Accurate classification of AF type is crucial for therapy planning and outcome prediction but remains limited by subjective diagnostic thresholds [34].

Heart Rate Monitors (HRMs) integrated with HRV analysis can provide initial rhythm assessments but often fail to distinguish supraventricular from ventricular arrhythmias. Newer HRMs (e.g., QardioCore) now offer multi-lead ECG acquisition during training and real-time cloud-based diagnosis [37]. Classification models can be extended to assess the impact of AF and AFL coexistence on symptom burden and QoL, helping tailor therapy for patients with high-risk symptom profiles [40].

PROMs and HR QoL instruments like ASTA enable non-invasive classification by symptom burden, particularly in differentiating AF and AFL patterns and their QoL impact [41]. Hypertension-linked bradyarrhythmias, such as those induced by degenerative conduction disease or OSA, can be detected and classified by soft computing systems considering clinical and signal features together.

Soft computing approaches have increasingly adopted hybrid models, such as the integration of Wavelet Transform and Teager Energy Operator to effectively capture nonlinear and nonstationary dynamics in ECG signals for enhanced arrhythmia classification. In athletic populations, heart rate monitors (HRMs) and heart rate variability (HRV) data, when combined with ECG snapshots, support real-time classification of rhythm irregularities under varying physiological conditions.

Furthermore, symptom-aware classification models have incorporated disease-specific instruments like the Arrhythmia-Specific Questionnaire in Tachycardia and Arrhythmia (ASTA) to evaluate health-related quality of life (HRQoL), particularly in patients with tachyarrhythmias. Comorbidity-aware classification frameworks are also gaining traction, aiming to identify arrhythmias in complex clinical populations such as those with hypertension, heart failure, and psychological conditions like anxiety or depression, highlighting the growing emphasis on holistic, patient-centric diagnostic modelling. The ASTA questionnaire, developed by a Swedish group [43], has been applied to classify tachyarrhythmia symptoms and evaluate health-related quality of life (HRQoL). This symptom-driven approach is particularly useful in clinical decision-making.

Soft computing techniques are also gaining traction in comorbidity-aware classification, particularly for patients with conditions like hypertension, heart failure, and psychological disorders (e.g., anxiety, depression). These multifactorial conditions introduce variability in ECG interpretation, emphasising the need for holistic, personalised models [45, 46]. According to the primary literature review discussed, future technical development is necessary to enhance arrhythmia classification with reduced noise in ECG signals. Accordingly, the research gaps are discussed in the next section of this thesis.

Table 2.9: Comparative Overview of Current Arrhythmia Classification Research

Author(s)	Dataset	Method/Technique	Reported Performance	Major Limitation
Sannino et al.	ECG datasets (WEKA platform)	SVM, RF, Decision Tree, WEKA-based ML	Good classification performance	Manual feature extraction required; automation through DL recommended
Xia et al.	Wearable ECG signals	Stacked Denoising Autoencoder (SDAE)	Robust denoised for wearable monitoring	Limited arrhythmia classification capability
Anwar et al.	ECG signals	DWT + Morphological Feature Extraction	Improved feature extraction	Not validated for high-risk arrhythmia prediction
Singh et al.	MIT-BIH	LSTM	Better binary classification accuracy	Limited to binary classification; further optimisation required
Singh et al.	ECG dataset	LSTM	Improved ECG classification	Suggested higher epochs and CNN integration for better accuracy
Marinho et al.	ECG signals	Soft Computing	Identification of abnormal ECG beats	Limited computational classification framework
Hannun et al.	Large real-world ECG dataset	End-to-End Deep Learning	High multi-class arrhythmia detection	Need for improved ECG denoising and more diverse datasets

A Novel Approach to classify Heart Arrhythmia using Deep Learning

Singh & Singh	ECG dataset	Feature Selection + SVM, RF, JRip	Improved classifier performance	Transition toward deep learning still required
Alarsan & Younes	Large-scale ECG data	Random Forest, Decision Tree, Hadoop	Scalable ECG classification	Limited comparison with modern DL architectures
Ganesh et al.	ECG dataset	Deep CNN (DCNN)	End-to-end classification	Computational complexity; dependence on large datasets
Qian et al.	ECG signals	FIR, IIR, VMD, EMD	Effective general denoising	Poor suppression of power-line interference
Hao et al.	ECG signals	Marginalised Particle Extended Kalman Filter (MP-EKF)	Effective ECG denoising	Performance degrades with abrupt heartbeat variations
Wang et al.	ECG signals	Denoising Autoencoder, WNN, FLNN	Improved adaptive denoising	WNN and FLNN effective only for specific noise types
Manju & Sneha	ECG signals	FIR, IIR, Kalman, Wavelet Filters	Improved Signal-to-Noise Ratio	Poor Gaussian noise removal
Gaamouri et al.	ECG signals	Dual Unscented Kalman Filter + MLP	Adaptive removal of Gaussian and muscle artifacts	Limited model generalisation
Mukhopadhyay & Krishnan	Wearable ECG	VMD + MP-EKF + k-NN	Good denoising and beat classification	Highly dependent on accurate beat classification
Singh & Pradhan	MIT-BIH	GAN-based ECG Denoising	Superior denoising over traditional filters	Limited evaluation on diverse clinical datasets
Mobile ECG Systems	Apple Watch, Kardia Mobile, QardioCore	Deep Learning + Mobile ECG Monitoring	Continuous real-time monitoring	Hardware limitations and dependence on signal quality

Table 2.10 Research Gap Analysis of Existing Arrhythmia Classification Methods

Research Aspect	Existing Studies	Identified Limitation	Proposed Work
ECG Denoising	FIR, IIR, Wavelet, EMD, VMD, MP-EKF	Unable to preserve ECG morphology under different noise conditions	Tuned Kalman Filter
Feature Extraction	Handcrafted Features, CNN, LSTM	Limited capture of both local and long-range ECG dependencies	Self-Attention Autoencoder
Classification	CNN, LSTM, Random Forest, SVM	Mostly optimise only the classification stage	Unified end-to-end framework
Validation	MIT-BIH, wearable datasets	Limited validation on real-time hospital ECG recordings	MIT-BIH + Real-time Hospital ECG
Computational Efficiency	Deep CNN, Transformer, LSTM	High computational complexity	Optimised lightweight architecture

3. Research Gap Identification

Based on the analysis, we have found some gaps; they are divided into technical points. Which found out the following points they are follow:

Gap 1: ECG Signal Denoising

Existing ECG denoising techniques, including Wavelet Transform (WT), Finite Impulse Response (FIR) filters, and conventional Kalman Filters, have demonstrated satisfactory performance in suppressing various types of ECG noise. However, these methods are generally evaluated under moderate noise conditions, typically ranging from +10 dB to -10 dB signal-to-noise ratio (SNR), and may introduce distortion to clinically significant ECG morphological features, thereby reducing the accuracy of subsequent arrhythmia classification. In contrast, the proposed Tuned Kalman Filter (TKF) is designed to preserve diagnostically important ECG morphology while effectively suppressing severe noise. The proposed method has been successfully validated under an extremely challenging noise condition of -30 dB SNR, demonstrating its robustness and superior denoising capability for highly corrupted ECG signals.

Gap 2: Feature Extraction

Most existing studies rely on CNN, LSTM, or handcrafted feature extraction methods, which may not effectively capture both local morphological characteristics and long-range temporal dependencies in ECG signals.

Gap 3: Integrated Framework

Most researchers improve either preprocessing or classification independently. Few studies develop an integrated framework that jointly optimises denoising, feature extraction, and classification.

Gap 4: Clinical Validation

Many deep learning models are evaluated only on benchmark datasets such as MIT-BIH. Their robustness on real-time hospital ECG recordings remains insufficiently investigated.

Gap 5: Computational Efficiency

Although deep learning models achieve high classification accuracy, many require substantial computational resources, limiting deployment in wearable or real-time monitoring systems.

Table 2.11 Research Gap Analysis

Literature Gap	Proposed Solution
ECG morphology distorted during denoising	Tuned Kalman Filter
CNN/LSTM limitations	Self-Attention Autoencoder
Separate preprocessing and classification	Unified end-to-end framework
Only benchmark datasets	MIT-BIH + Real-time hospital ECG
High computational complexity	Optimized architecture

Based on the critical analysis of the existing literature, it is evident that no single framework simultaneously addresses adaptive ECG denoising, attention-based feature learning, integrated preprocessing and classification, computational efficiency, and validation on both benchmark and real-time clinical datasets. These limitations constitute the primary research gaps that motivate the proposed study.

2.4 Chapter Summary:

This chapter presents a detailed literature review on ECG signal denoising and arrhythmia classification techniques, organised into three main methodological domains: Machine Learning (ML), Deep Learning (DL), and Soft Computing. Initially, it addresses the challenges of noise in ECG signals—such as baseline wander, muscle artifacts, and power-line interference—and outlines traditional ML-based filters (FIR, IIR, Kalman) and hybrid methods (e.g., UKF-MLP and MP-EKF) for their mitigation. DL approaches, such as Stacked Denoising Autoencoders and GANs, are highlighted for their adaptability and success in preserving ECG morphology under noisy conditions, including their deployment in wearable and mobile platforms like QardioCore. Soft computing techniques, including Wavelet Transforms, Empirical Wavelet Transform (EWT), and hybrid models combining fuzzy logic and neural networks, are recognised for their ability

to handle nonlinear, uncertain noise environments. The chapter then transitions to arrhythmia classification, evaluating traditional ML classifiers (SVM, RF, JRip), DL models (CNNs, LSTMs), and soft computing-based classifiers enriched by symptom data and PROMs (e.g., ASTA questionnaire). Finally, the chapter identifies key research gaps such as the need for unified denoising frameworks, real-time wearable solutions, multi-label classification systems integrating clinical metadata, and QoL-informed classification approaches for more personalised, robust, and clinically relevant ECG analysis.

CHAPTER 3

ARRHYTHMIA CLASSIFICATION METHODS BASED ON ML/DL TECHNIQUES

3.1. Literature Analysis Process

We followed systematic methods to generate literature databases. Initially, we identified major electronic databases, such as Elsevier, Springer, and IEEE, for primary publication searches using the phrase “cardiac arrhythmias”. The following search string was appended and applied:

ML or heart arrhythmia risk or DL and Artificial Intelligence (AI)

Table 3.1 displays the results of the aforementioned query across the chosen databases.

Table 3.1: Shortlisted Literature Across Elsevier, Springer, and IEEE Sources

Input String	Database	Conferences	Journals / Magazines	eBooks	Miscellaneous	Total Publications
ML and KF	Elsevier	105	198	8	4	315
	Springer	214	216	6	0	436
	IEEE	159	204	0	N/A	363
Heart arrhythmia risk	Elsevier	12	48	0	0	60
	Springer	59	87	1	0	147
	IEEE	21	91	0	N/A	112
	Elsevier	41	96	0	0	137
	Springer	97	192	0	5	294

Deep Learning	IEEE	176	83	0	N/A	259
Artificial Intelligence	Elsevier	23	98	0	0	121
	Springer	47	106	0	5	158
	IEEE	86	76	0	N/A	162
Total Publications	Elsevier	239	681	10	19	949
	Springer	722	840	7	12	1,581
	IEEE	444	470	0	N/A	914

Data Extraction Criteria

In the second stage, we examined conference and journal paper titles (eBooks and miscellaneous are omitted). We have shortlisted publications as research references out of the 920 (Elsevier), 1562 (Springer), and 914 (IEEE). We have also shortlisted 96 publications from Taylor and Francis and the Wiley library for the publication year 2021 onwards to capture the COVID-19 impact on cardiac arrhythmias. As a preliminary search, publications from online libraries were analysed; articles unrelated to our field of study were rejected, and publications with multiple abstract similarity data that were published in multiple databases were also rejected.

After filtering the unique data according to our intended research domain, we produced 123 documents that were immediately relevant to our task. Heart arrhythmia, machine learning, deep learning, clinical trial implications, automation

in healthcare, Kalman filter, and other topics were the most important. Figure 3.1 shows the graphical representation of bibliographic percentages.

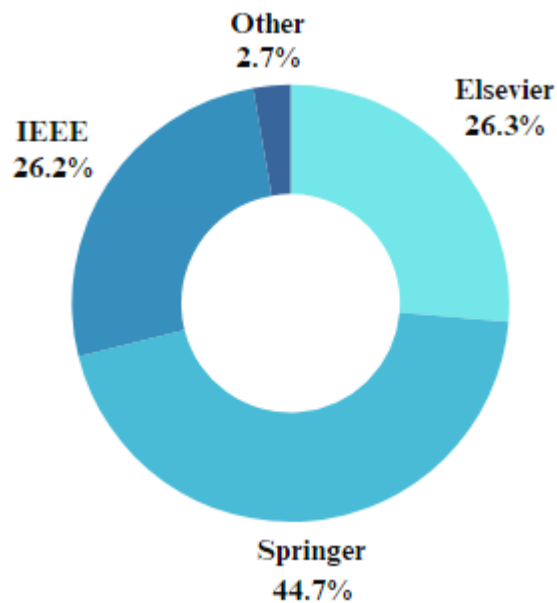


Figure 3.1: Bibliographic Representation of Literature Database

Bibliographic Quality Assessment

The following criteria were used to evaluate the shortlisted papers:

Q1: Is an index of publications from journals acceptable?

Q2: Will other researchers continue to credit the author's work beyond 2024?

Q3: Is the study the author is doing about cardiac arrhythmias?

The following is the synchronisation of the quality evaluation responses:

Answer 1: Indeed. However, before the year 2000, authors also referred to print periodicals. As a result, we did not include articles before 2017.

Answer 2: Indeed. There is a research citation record up to 2024, and the original referenced paper makes extensive use of cross-references.

Answer 3: Indeed. In the field of heart arrhythmia research, the authors represented a multifaceted investigation.

3.2. Secondary Literature Review

The secondary literature review aims to study the existing DL/ML methods incorporating cardiac arrhythmia classification.

According to the author's analysis, incorporating symptoms of anxiety and depression into a multi-adjusted logistic regression model for atrial fibrillation (AF) prediction did not improve its performance, as the AUC values remained nearly identical (0.8504 without and 0.8506 with these symptoms) [45]. Similarly, the presence of heart failure (HF) in AF patients did not significantly alter the frequency of symptoms, although symptom presentation tended to be more severe and atypical in HF patients. Factors such as diabetes, myocardial infarction, and male gender were associated with asymptomatic AF cases. These findings underscore the complexity of AF symptomatology and the need for data-driven tools to support diagnosis. Artificial intelligence (AI), particularly its subsets ML and DL, has emerged as a transformative solution for handling such complex clinical data. ML identifies both linear and nonlinear patterns in data, often requiring substantial feature engineering. For instance, in one study, ECG signals were converted into spectrograms using wavelet transforms, and handcrafted features were fed into a random forest model to predict impaired myocardial relaxation [46].

In contrast, DL eliminates manual feature extraction by learning representations directly from raw data. Multiple convolution and pooling layers are used by

DCNNs, the most popular DL architecture in ECG classification, to identify hierarchical features. Fully connected layers are then used for the final prediction. The ability of CNNs to process ECG data end-to-end has made them increasingly popular in cardiovascular diagnostics. These architectures can detect subtle and high-dimensional patterns, making them superior to traditional models in many clinical applications. Furthermore, large-scale datasets and improvements in processing power have benefited DL models by enabling real-time, highly accurate predictions [47].

Conventional ML techniques, including LR, SVM, KNN, RF, DT, and Naïve Bayes (NB), have been used in many studies to detect arrhythmias based on structured datasets, including MIT-BIH, NCKU-CBIC, and MIMIC-IV. In one of the comparative studies, LR achieved the best accuracy of 87% in predicting heart disease-related arrhythmias, followed by DT (83%), SVM (81%), and NB (80%) [73]. The Random Forest model trained using Synthetic Minority Oversampling Technique (SMOTE) achieved 94.65% accuracy and an AUC of 0.8956 in pediatric arrhythmia classification [55]. An ensemble approach combining Multi-Kernel Extreme Learning Machine (MKELM) and RF using a one-vs-one scheme provided 98.1% accuracy and 93.9% positive predictive value on the MIT-BIH dataset [56]. RF-based feature importance analysis also identified key clinical indicators such as sodium, calcium, and potassium levels, which, after optimisation with Grid Search and Genetic Algorithms, resulted in an AUC of 0.9787 [57]. Furthermore, RF models outperformed CHADS₂ and CHA₂DS₂-VASc scores in predicting thromboembolic events among patients with non-valvular AF [58]. SVM with mRMR feature selection was shown to perform favourably in multiclass

arrhythmia detection [61], and wavelet-SVM ensemble differentially classified ARR, CHF, and NSR classes, achieving 98% test accuracy [70]. On the UCI dataset, binary and 16-class arrhythmias were classified using a fuzzy fusion ensemble model that combined features selected by multiple algorithms [69].

The MIT-BIH database of arrhythmias continues to be a baseline benchmark for arrhythmia research. Classic ML models based on this dataset have high performance, including a Random Forest model with SMOTE that attained 94.65% accuracy [55]. Kernelized SVM using PCA and Random Oversampling showed better performance, as high as 99.52% [75]. Among DL models, hybrid models such as CNN-LSTM and RRHOS-LSTM showed excellent classification accuracy (95.81%) on MIT-BIH employing weighted loss functions and a meta-classifier strategy [59]. A Recurrent CNN optimised using Grey Wolf Optimisation (GWO) performed better than all the compared models (DT, KNN, RF, SVM, LR) with 98% classification accuracy [74]. Lightweight CNN models integrating long-term heart rate information attained 98.5% on MIT-BIH and 97.1% on NCKU-CBIC [80]. In a different example, CNN models integrated into cloud-computing systems for real-time visualisation and recognition attained 98.32% accuracy with MIT-BIH and 97.1% with NCKU-CBIC datasets [78].

Sophisticated DL models with CNN and LSTM architectures have greatly enhanced arrhythmia classification. An industrial-strength test on 65,932 multilead ECG recordings from 38,899 patients, annotated by cardiologists, used LSTM networks to achieve 90% accuracy in classifying 12 rhythms, outperforming emergency physicians' diagnostic skills [60]. Another new model, 3DECG-Net, converted 12-lead ECGs to 3D representations via recurrence plots and utilised a

multi-head attention residual network with a micro F1-score of 80.3% [76]. Flamingo Optimisation was applied to a DCNN model to optimise hyperparameters for IoT-based ECG data, achieving 98.5% accuracy [68]. DSE-ResNet, incorporating Detached Squeeze-and-Excitation blocks, attained an F1-score of 0.817 on the CPSC2018 dataset [65]. Explainable AI methods such as LIME and SHAP were employed to detect feature contributions and lead-specific effects, boosting clinical confidence in model predictions [76], [77].

Due to the episodic character of arrhythmias and difficulties in ECG recording, PPG has come under scrutiny for its non-invasive utilisation. A recent study proposed new morphological features derived from PPG signals for the identification of various arrhythmias with rule-based and statistical methods, achieving accuracies of 98.43%/94.16% (retrospective) and 94.16%/93% (prospective) datasets [71].

Cloud-integrated and hardware-embedded systems have real-time ECG classification functionality. A web-based system attained 98.32% and 97.1% accuracies based on MIT-BIH and NCKU-CBIC datasets, respectively. The embedded AI accelerator employed hybrid stationary methods for enhanced data reuse and power minimisation [78]. Likewise, ultra-lightweight CNN parallel processing integrated architecture attained 98.5% accuracy and was energy-efficient optimised [80].

Early diagnosis of VF can greatly improve outcomes. Ensemble classifiers, using the NSR and SCDH datasets, detected VF up to 50 minutes before occurrence with over 99% accuracy. When tested 50 minutes before and after VF onset, the model

achieved 90.3% accuracy in pre-episode detection, among the highest recorded performances [81].

Research has also explored the impact of psychological factors and comorbidities on AF diagnosis. AF patients with HF were found to exhibit more severe and atypical symptoms compared to those without HF, despite having the same symptom frequency. Factors such as diabetes, male gender, and history of MI facilitated asymptomatic presentations [45]. Psychological conditions like anxiety and depression did not significantly influence AF risk, as indicated by logistic regression AUC values remaining nearly unchanged (~ 0.8504) whether symptoms were included or not [45].

A large systematic literature review (SLR) of 494 studies (2017–2023) used PRISMA 2020 methodology and bibliometric analysis to examine trends in DL-based ECG classification. It showed a shift away from manual feature engineering toward auto-generated deep learning and emphasised the importance of wearable technologies, mobile health, and big data in the future of arrhythmia diagnostics [83]. Another survey described the development of arrhythmia classification, starting from classical ML and progressing to hybrid DL, highlighting each method's advantages, limitations, and applicability in real-world clinics.

Heart arrhythmia classification often uses ECG signal analysis, but it also uses ML and DL methods. These methods involve preprocessing the ECG signal, extracting relevant features, and then using various algorithms to classify different types of arrhythmias.

3.2.1. ECG Analysis:

The electrical activity of the heart is measured by an ECG, which records the waves and rhythm that show whether a heartbeat is normal or pathological. To guarantee proper analysis, the raw ECG signal must be cleaned of noise and baseline drift during the signal processing step. For signal processing, methods like the Savitzky-Golay filter, Kalman filter, DWT, median filters, etc., are frequently used. The standard representation of ECG signal classification is shown in Figure 3.2.

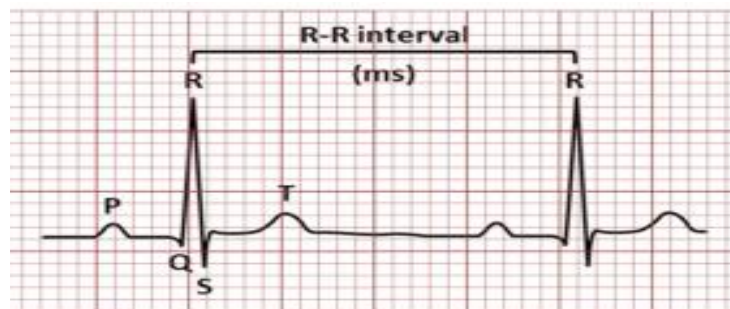


Figure 3.2: Representation of the ECG signal interval [101]

Further, key features can be extracted from the ECG signal by analysis of:

- **Heart Rate Variability (HRV):**

HRV is a tiny variation in heartbeats between different intervals, which is a fraction of a second added or subtracted between beats in these minuscule fluctuations, and can be detected with only specialist equipment. Even though HRV exists in healthy people, it will nonetheless be a sign of mental health concerns, including anxiety and depression, as well as cardiac abnormalities. Heart rate fluctuation itself is not an arrhythmia; rather, it is a natural occurrence. The term "sinus rhythm" refers to the regular heartbeat that occurs with "sinus arrhythmia" when the heart beats regularly over 0.12 seconds of variation between beats. Heart rate variability can sometimes meet criteria for sinus arrhythmia.

The most common cause of sinus arrhythmia is breathing, which is a usual response of the heart and circulatory system. When sinus arrhythmia isn't caused by breathing, it indicates another cardiac condition that requires medical attention. Low heart rate variability is an indication of present or potential health issues since it indicates that the body is less adaptable and has trouble adjusting to new circumstances. Additionally, those with higher resting heart rates are more likely to experience it because when the heart beats faster, there is less time between beats, which reduces the possibility of variability. This is commonly seen in conditions like diabetes, high blood pressure, heart arrhythmia, asthma, anxiety, and depression.

In medical contexts, an ECG, sometimes referred to as an EKG, is frequently used to track heart rate variability. To identify the electrical activity of the heart, the device uses precise sensors that are affixed to the chest. To continuously monitor heart rate variability over long periods of time, doctors also provide their patients with portable equipment. Patients may record data for a few minutes or a full day, depending on the requirement; longer monitoring periods typically yield the most trustworthy information.

- **Morphological Features:** Analysing the shape and characteristics of ECG waves. Heart analysis through morphological features involves examining the structure and shape of the heart, including its chambers, valves, and blood vessels. This assessment was done using various imaging techniques and microscopic examination of tissue samples.

In arrhythmia analysis, morphological features are aspects of the electrical activity of the heart (as recorded by ECG or PPG signals [Photoplethysmography]) that are

associated with the form and shape of the heartbeats. These features, distinct from rhythm-related features (like heart rate variability), are used to identify and classify different types of arrhythmias.

While rhythm features (like heart rate variability) focus on the timing of heartbeats, morphologic features capture the shape and form of the individual heartbeats, providing a more comprehensive picture of cardiac activity. Morphological features are often used as inputs for ML algorithms to classify arrhythmias and predict their severity.

- **RR Interval:** Measuring the time between consecutive R waves, which can indicate heart rhythm abnormalities.
- **Statistical Features:** Calculating statistics like mean, median, and standard deviation of RR intervals or other extracted features.

3.2.2. ML and DL Techniques:

Once features are extracted, various ML algorithms are used by the authors to classify the ECG signals into different arrhythmia types. Existing techniques include:

- **SVM:** A popular choice for ECG-based arrhythmia classification.
- **KNN:** An algorithm that categorises data points according to their proximity to other data points is straightforward but efficient.
- **DT:** A tree-like structure that makes decisions based on feature values.
- **Ensembles:** Combining multiple classification algorithms to improve accuracy.

- **DL:** CNNs used for feature extraction and classification directly from the ECG signals.

Further, Table 3.2 shows the key findings of existing signal pre-processing methods.

Table 3.2: Existing Signal Pre-Processing Methods

Sr. No	Ref. No.	Author, Year	Method	Findings/ Research Gaps
1	[84]	Khatar, Zakaria, Dounia Bentaleb, and Saadia Drissi, 2025	Butterworth, Daubechies Wavelet, Savitzky-Golay filter, and Chebyshev Type II	SNR value not measured
2	[85]	Hesar, Hamed Danandeh, and Amin Danandeh Hesar, 2024	Adaptive augmented cubature Kalman filter/smoothing (CKF/CKS)	Improved SNR (27.8910)
3	[86]	Elouaham, Samir, et al., 2024	The author used two ECG databases from MIT-BIH, which contain a variety of cardiac signals and noise levels, applied DWT-ADTF, FST, Kalman, Liouville–Weyl fractional compound integral filter LW, Weiner, and EWT denoising techniques.	Improved SNR (27.6265) and minimised MES (0.0007)
4	[87]	Bai, Xiangyun, et al., 2024	Kalman filtering and wavelet transform applied for CNN multi-head attention model analysis.	SNR value not measured
5	[88]	Curtis, Aaron et. al., 2023	The author used compressed sensing with a Kalman filter for cardiac signal reconstruction.	Visual cardiac signal reconstruction accomplished.
6	[89]	Kim, Namho, et al., 2023	The authors proposed Wavel Net, a unique CNN architecture that uses wavelet transforms to accomplish spectral analysis.	The WaveletNet-based model achieved over 90% classification accuracy, demonstrating high sensitivity for non-ectopic, supraventricular ectopic, and ventricular ectopic beats.

7	[90]	Gon, Anusaka, and Atin Mukherjee, 2023	The author used lifting-based DWT for signal preprocessing in an FPGA-based architecture for R-peak detection.	SNR value not measured
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Further, existing models are studied that collaborate with signal processing for ECG analysis.

By gathering a sizable dataset of 661 Holter recordings and labelling them by a qualified cardiologist, the author created a residual DL model. To capture long-range dependencies and complex temporal linkages that are essential for spotting minor patterns suggestive of AF, the DL model made use of attention mechanisms. With an AUC-ROC of $AUC = 0.967$, experimental findings showed that the suggested model obtained a better sensitivity, specificity, and AUC when tested using an external test dataset, especially IRIDIA-AF [91]. Figure 3.3 gives the standard reference of a residual deep learning attention-based model.

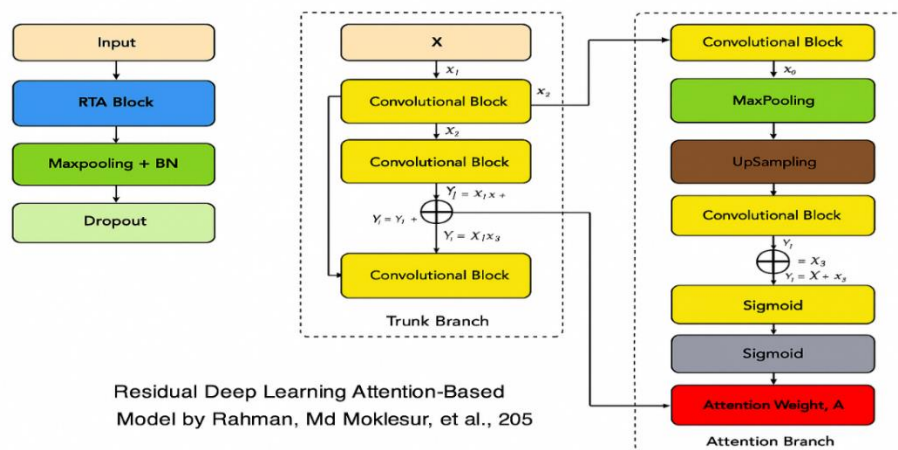


Figure 3.3: Residual Deep Learning Attention-Based Model [91]

The standard workflow of Figure 3.3 of the residual deep learning attention-based model is shown as follows: The ECG signal is first pre-processed to remove noise and

normalise the input. The processed signal is then passed through a Residual Attention Network consisting of a trunk branch for hierarchical feature extraction and an attention branch for generating attention weights. The attention mechanism enhances diagnostically relevant ECG features while suppressing irrelevant information. Finally, the refined feature maps are classified through a fully connected layer and Softmax classifier to predict the corresponding arrhythmia class.

The author used a Hierarchical Attention Network (HAN) to classify texts in an ECG-based categorisation. Two attention layers in the adapted HAN concentrate on different-sized ECG data segments. The author conducted a comparative analysis between the adapted HAN and state-of-the-art architectures, featuring a network with convolution, attention, and transformer layers. Comparable test accuracy is shown by the modified HAN, which also offers improved interpretability analysis and notable model complexity reductions: The modified HAN achieves 98.55% test accuracy for the MITBIH dataset [92]. Figure 3.4 gives the standard reference of the residual deep learning attention-based model of Rodriguez in 2025. The proposed hierarchical attention-based LSTM framework first divides the ECG signal into multiple sequences, which are further partitioned into smaller segments. Each segment is processed using a segment-level LSTM to learn temporal features, while a segment attention mechanism assigns importance weights to emphasize diagnostically relevant segments. The resulting sequence representations are then processed by a sequence-level LSTM, followed by a sequence attention mechanism that identifies the most informative sequences. Finally, the aggregated high-level feature representation is passed through a fully connected layer and a Softmax classifier to predict the corresponding arrhythmia class. This hierarchical architecture effectively captures both local and global temporal dependencies, leading to improved ECG classification performance

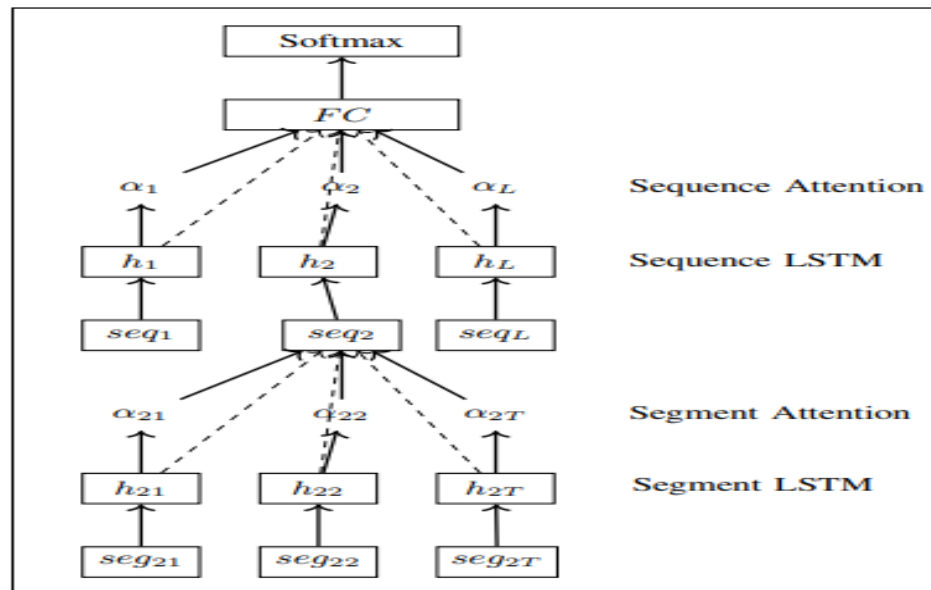


Figure 3.4: Residual Deep Learning Attention-Based Model [92]

The author considers a single-lead ECG-based network, and a planned convolution, attention, and transformer-based network (CAT-Net) shows capable performance on arrhythmia classification, capturing the morphological features of local and global heartbeats. In the MIT-BIH dataset, CAT-Net achieves a better macro F1 score for 5-class arrhythmia classification [93].

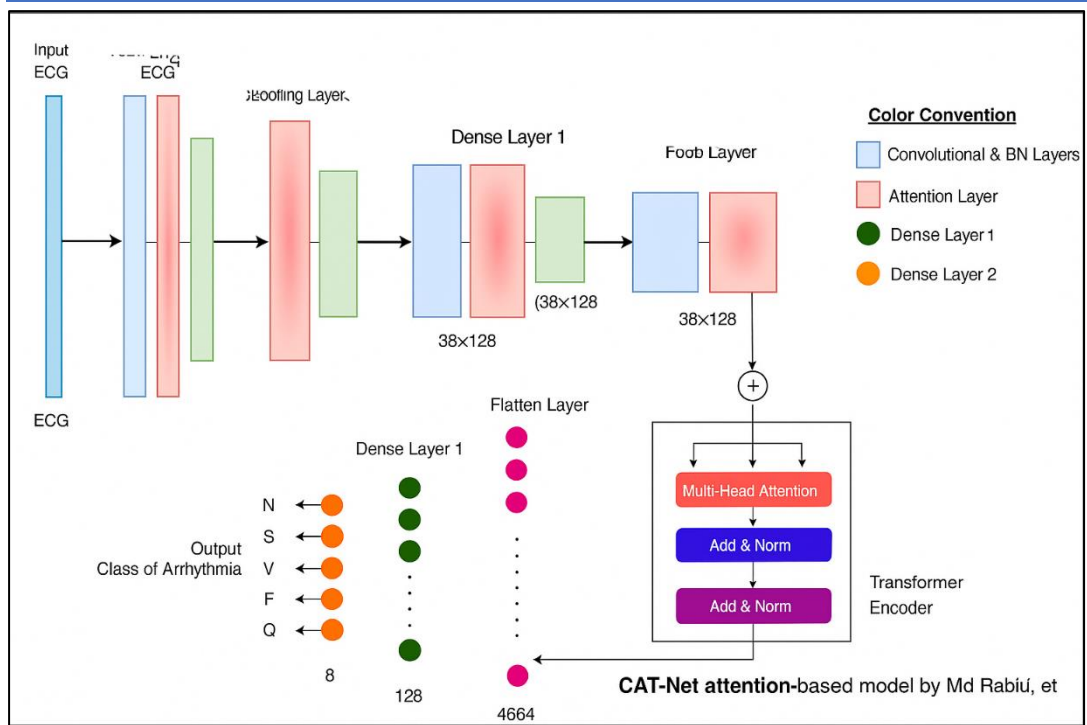


Figure 3.5: CAT-Net Attention-Based Model [93]

Figure 3.5 gives the standard reference of the CAT-Net attention-based model. Two distinct features set the dual-branch convolutional neural network through domain-informed attention apart. A dual-branch network is initially used to extract limb and precordial leads' intra-group similarities and differences. Then, a domain-informed attention mechanism is introduced that incorporates numerous RR wave intervals and critical domain information from ECG into coordinated attention to successfully capture the domain's properties and adaptively assign attention weights to significant portions. This method produces a better F1-score and a macro-AUC, per experimental results.[94]. The author created a technique that uses a CNN to extract time-invariant features and a Sequence-To-Sequence (seq2seq) based on a Bidirectional Long Short-Term Memory (BiLSTM) network enhanced with an Attention Mechanism (AM) to categorise the heartbeats. The author used the MIT-BIH arrhythmia database [95]. The figure illustrates the workflow of the CAT-Net attention-based model for ECG

arrhythmia classification. Initially, the input ECG signal is processed through convolutional and batch normalisation layers to extract local morphological features. Attention layers are incorporated after the convolutional blocks to emphasise diagnostically important ECG regions while suppressing irrelevant information. Max-pooling reduces the spatial dimension of the learned features, which are then transformed into high-level feature representations through dense layers. These representations are forwarded to a Transformer encoder comprising multi-head self-attention, residual connections, feed-forward networks, and layer normalisation to capture long-range temporal dependencies within the ECG signal. Finally, the transformer output is flattened, processed through fully connected layers, and classified using a Softmax layer into one of the predefined arrhythmia classes (Normal, Supraventricular, Ventricular, Fusion, or Unknown). This hybrid CNN–Attention–Transformer architecture effectively combines local feature extraction with global contextual learning, improving the robustness and accuracy of arrhythmia classification.

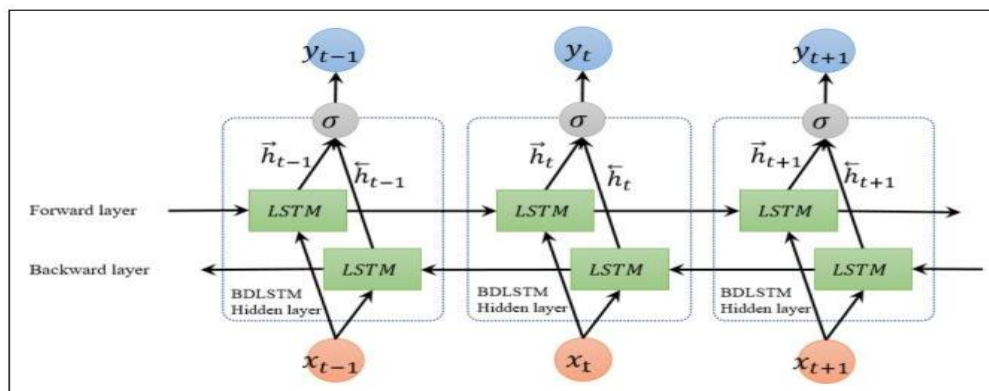


Figure 3.6: Bilstm Attention-Based Model [134]

Figure 3.6 illustrates the workflow of the Bidirectional Long Short-Term Memory (BiLSTM) network used for ECG sequence modelling. The input ECG signal is represented as a sequence of temporal samples and simultaneously processed by

two LSTM networks operating in opposite directions. The forward LSTM captures temporal dependencies from past to future, while the backward LSTM learns contextual information from future to past. At each time step, the hidden states from both directions are concatenated to form a comprehensive feature representation that incorporates both preceding and succeeding ECG information. The concatenated features are passed through an activation function and then to a fully connected layer, where high-level discriminative features are learned. Finally, a Softmax classifier computes the class probabilities and predicts the corresponding arrhythmia category. By leveraging bidirectional temporal information, the BiLSTM model effectively captures both local and long-range dependencies in ECG signals, leading to improved classification accuracy and robustness.[96]

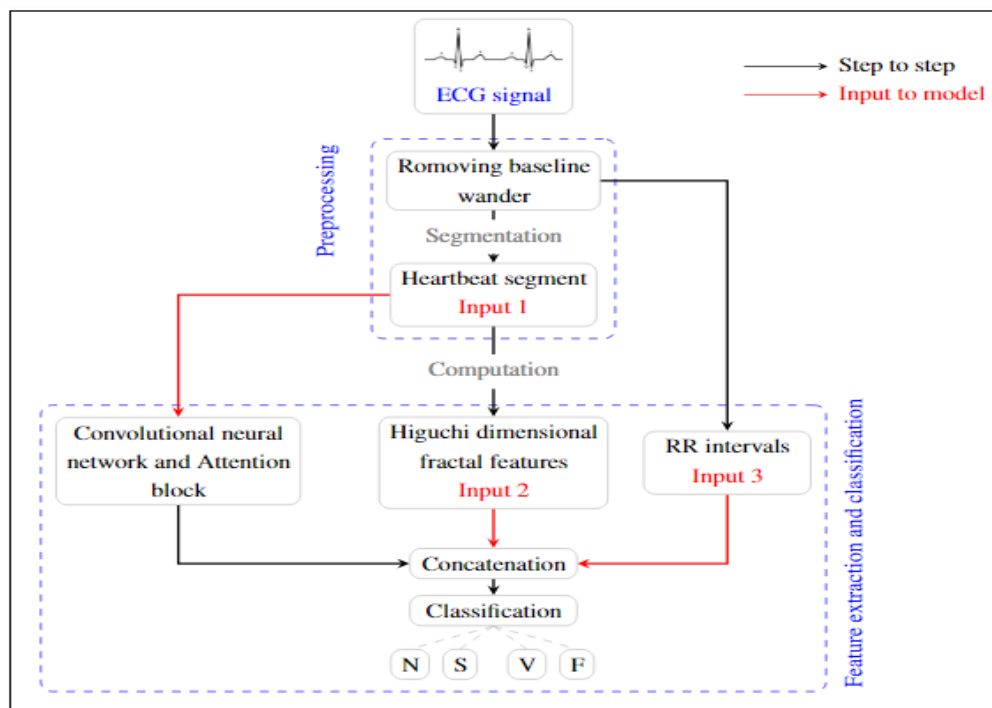


Figure 3.7: Bilstm Attention-Based Model [96]

Figure 3.7 refers to the BiLSTM attention-based model. The author created a deep learning model that combines attention processes with multi-stream convolutional recurrent neural networks. This model was enhanced using clustering techniques and a data augmentation method based on generative adversarial networks. Pre-processing, feature extraction using the MuDANet model, and data augmentation utilising the cutting-edge DBSCAN-GAN technique are the three main steps of the algorithm. A two-step denoising and filtering procedure is used in the pre-processing stage to greatly improve the ECG signals. The attention model's F1-score was 0.876, but after 10-fold cross-validation used to supplement data, it rose to an astounding 0.962 [97].

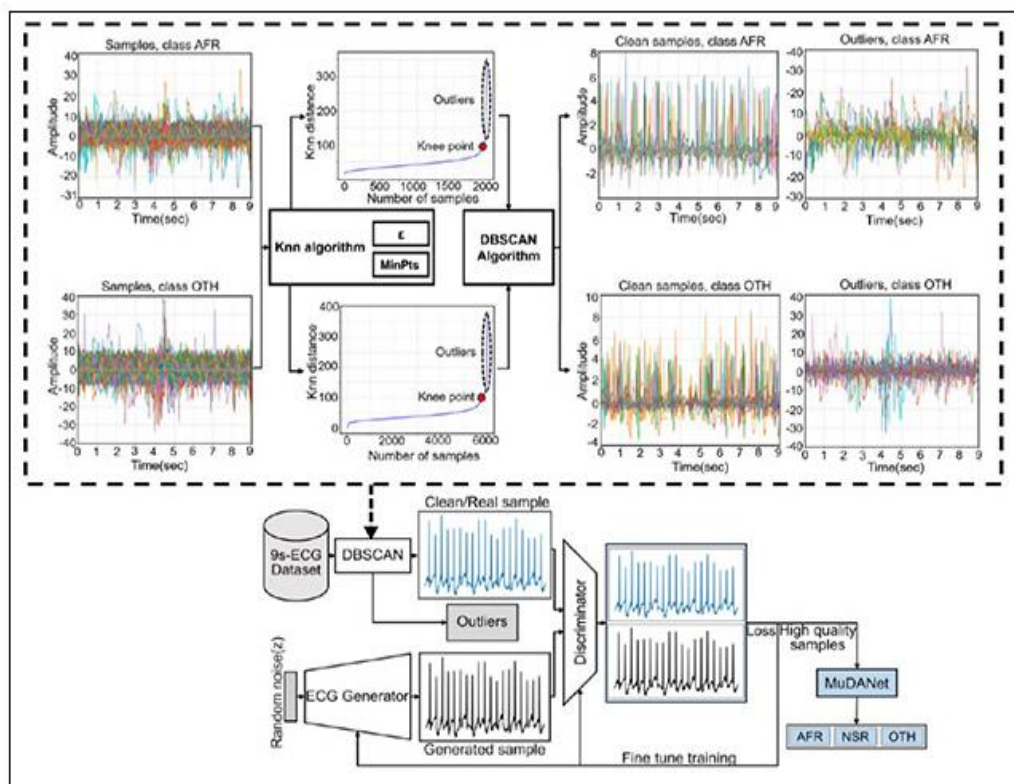


Figure 3.8: DBSCAN Attention-Based Model [97]

Figure 3.8 illustrates the workflow of the proposed DBSCAN-GAN-MuDANet framework for ECG arrhythmia classification. Initially, ECG recordings from the 9s-

ECG dataset are analysed using a K-nearest neighbour (KNN) distance graph to estimate the optimal DBSCAN parameters (ϵ and MinPts). The DBSCAN algorithm is then employed to identify and remove noisy or outlier ECG samples, resulting in a clean dataset suitable for model training. Subsequently, a Generative Adversarial Network (GAN) generates realistic synthetic ECG signals from random latent vectors to augment the training data and address class imbalance. The generated signals are evaluated by a discriminator, and only high-quality synthetic samples are retained through adversarial training. Finally, the refined dataset, comprising clean real samples and high-quality generated samples, is used to train the MuDANet classifier, which predicts the ECG rhythm into one of the predefined classes, namely Atrial Flutter/Fibrillation (AFR), Normal Sinus Rhythm (NSR), or other rhythms (OTH). This integrated framework enhances data quality, increases dataset diversity, and improves the robustness and classification accuracy of the deep learning model[98]

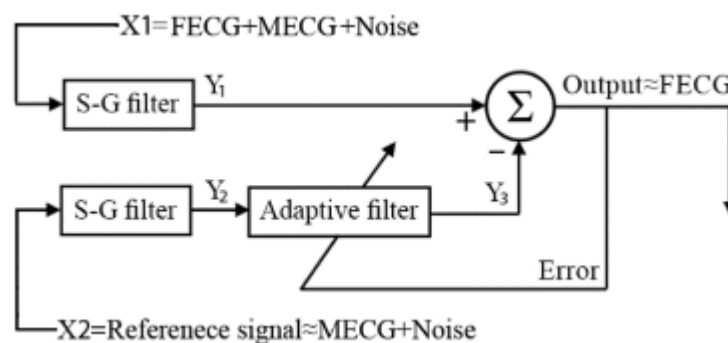


Figure 3.9: Savitzky-Golay Filter Function [98]

Figure 3.9 Golay Filter uses the EWT method to preserve signal information while successfully removing noise. The research uses MIT-BIH, which has two ECG databases, contains a variety of cardiac signals and noise levels, and applies DWT-ADTF, FST, Kalman, Liouville–Weyl fractional compound integral filter LW, Weiner, and EWT denoising techniques [99]. Figure 3.9 presents the workflow of

the proposed fetal ECG extraction framework based on the Savitzky–Golay (S-G) filter and an adaptive filter. Two synchronised input signals are considered: a primary abdominal ECG containing the fetal ECG, maternal ECG, and noise, and a reference signal consisting primarily of the maternal ECG and background noise. Initially, both signals are smoothed using Savitzky–Golay filters to reduce high-frequency noise while preserving the morphological characteristics of the ECG waveform. The filtered reference signal is then processed by an adaptive filter, which estimates the maternal ECG component present in the primary signal. The adaptive filter iteratively updates its coefficients using an error-feedback mechanism to improve the estimation accuracy. Finally, the estimated maternal ECG is subtracted from the filtered primary signal, leaving an output that predominantly represents the fetal ECG. This hybrid filtering strategy effectively suppresses maternal interference and noise while preserving the diagnostic features of the fetal ECG, thereby improving signal quality for subsequent analysis.

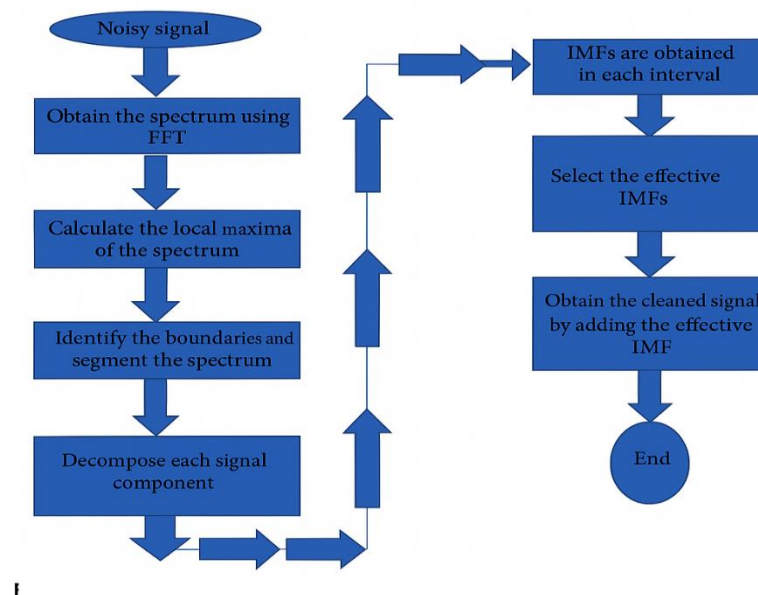


Figure 3.10: Flow diagram of the empirical wavelet transforms method [86]

Figure 3.10 illustrates the workflow of the FFT–EMD-based signal denoising method. Initially, the noisy signal is transformed into the frequency domain using the Fast Fourier Transform (FFT) to analyze its spectral characteristics. The local maxima of the spectrum are then identified, and the spectrum is segmented into multiple frequency intervals based on these peak locations.[100] Each segmented frequency component is independently decomposed using Empirical Mode Decomposition (EMD), producing a set of Intrinsic Mode Functions (IMFs). The resulting IMFs are evaluated according to predefined criteria, such as energy distribution, correlation, or signal-to-noise ratio, to distinguish informative components from noise-dominated components. Only the effective IMFs are retained and summed to reconstruct the denoised signal. This adaptive decomposition and reconstruction process effectively suppresses noise while preserving the essential characteristics of the original signal, thereby enhancing its quality for subsequent feature extraction and classification[101]

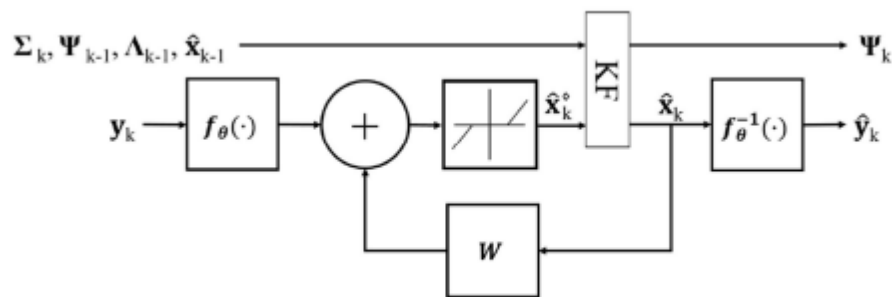


Figure 3.11: Flow Diagram of The Kalman Filter Processing [100]

Figure 3.11 illustrates the workflow of the proposed deep learning-assisted Kalman filtering framework. Initially, the Kalman filter is initialised using the previous state estimate, covariance matrix, and state transition model. At each time step, a noisy measurement is received and transformed into a latent feature representation

through a nonlinear neural network encoder. The encoded features are combined with a process noise model to generate an initial state prediction, which is subsequently refined by the Kalman filter through recursive prediction and correction stages. During the correction phase, the Kalman gain is computed to optimally balance the predicted state and the incoming measurement, thereby minimising estimation error. The updated hidden state is then passed through a neural network decoder to reconstruct the denoised or estimated signal in the original observation space. Finally, the updated state variables are propagated to the next iteration, enabling continuous recursive estimation. By integrating nonlinear feature learning with optimal Bayesian filtering, the proposed framework effectively improves state estimation accuracy and robustness in noisy signal environments.

Table 3.3 Comparative Analysis of Existing ML/DL Techniques

Method	Strength	Limitation
CNN	Excellent local feature extraction	Cannot effectively model long-term temporal dependencies
LSTM	Learns temporal information	Weak at extracting local morphological features
BiLSTM	Utilizes past and future context	Higher computational complexity
Attention	Focuses on important ECG regions	Depends on quality of extracted features
Transformer	Captures long-range dependencies	Requires large datasets and high computational resources
CNN-LSTM	Learns spatial and temporal features	May still overlook nonlinear signal complexity
Hybrid ML Methods	Lower computational cost	Limited automatic feature learning

Although CNN-based methods effectively capture local morphological features, they often fail to represent long-term rhythm information. LSTM and BiLSTM models improve temporal modelling but have limited capability in extracting detailed morphological characteristics. Transformer-based approaches achieve promising performance by modelling long-range dependencies; however, they require large training datasets and significant computational resources. Furthermore, many existing studies rely solely on deep learning or handcrafted features, without exploiting their complementary strengths. These limitations indicate the need for a hybrid framework capable of integrating morphological, temporal, and nonlinear ECG characteristics while maintaining computational efficiency.

3.4 Chapter Summary

This chapter explored a wide range of cardiac arrhythmia classification methods using both ML and DL techniques, based on a systematically curated literature dataset. Traditional ML models, including LR, SVM, RF, and NB, demonstrated competitive performance in structured ECG datasets such as MIT-BIH and MIMIC-IV, especially when enhanced with preprocessing, feature selection, and ensemble strategies. Meanwhile, DL approaches like CNNs, LSTMs, and hybrid CNN-LSTM models achieved superior accuracy and generalisation, particularly when trained on large-scale datasets. CNN-based architectures enabled automatic hierarchical feature learning, reducing reliance on handcrafted features, while attention mechanisms and optimisation algorithms such as Grey Wolf and Flamingo metaheuristics further improved performance. Cloud and hardware-accelerated platforms enabled real-time ECG processing with high accuracy and low power requirements. Emerging technologies such as PPG and explainable AI further expanded the scope of

arrhythmia detection. Despite these advancements, gaps remain in handling imbalanced datasets, reducing dependency on large, labelled datasets, improving model interpretability, and deploying energy-efficient wearable systems for continuous, real-time monitoring. These gaps highlight the need for further innovation in integrating ML/DL with clinical workflows for robust, scalable arrhythmia diagnostics. Hence, we presented the proposed pre-processing of ECG data in the next Section 4.2.2 of this thesis.

Table 3.4 Comparison Table of Methods

Aspect	Machine Learning (ML)	Deep Learning (DL)
Feature Extraction	Manual (handcrafted)	Automatic feature learning
Training Time	Low to Moderate	High
Inference Time	Low	Moderate to Low (after training)
Computational Complexity	Generally Low	High
Memory Requirement	Low	High
Hardware Requirement	CPU is usually sufficient	GPU/TPU preferred
Number of Parameters	Few	Millions (depending on architecture)
Performance on Small Datasets	Good	May overfit
Performance on Large Datasets	Limited	Excellent
Ability to Learn Complex Features	Limited	Excellent
ECG Morphology Learning	Depends on engineered features	Learns automatically

Table 3.5 Computational Complexity of Common Algorithms

We also include a table summarising the approximate computational complexity.

Algorithm	Approximate Training Complexity	Comments
KNN	Training: $O(1)$; Prediction: $O(nd)$	No explicit training; prediction is costly.
Decision Tree	$O(nd \log n)$	Efficient for moderate datasets.
Random Forest	$O(T, nd \log n)$	(T) is the number of trees.
Naïve Bayes	$O(nd)$	Computationally efficient.
SVM (RBF kernel)	Between $O(n^2)$ and $O(n^3)$	Expensive for large datasets.
CNN	Approximately proportional to $\text{epochs} \times \text{samples} \times \text{convolution operations}$	Complexity depends on network depth and filter sizes.
LSTM	Approximately proportional to $\text{epochs} \times \text{samples} \times \text{hidden units}^2$	Sequential computations increase training time.
BiLSTM	Roughly twice the cost of LSTM	Processes sequences in both directions.
Transformer	Self-attention has $O(n^2)$ complexity with respect to sequence length	Powerful but computationally intensive.

Rather than presenting only a table, include a short analytical discussion such as:

Machine learning algorithms generally exhibit lower computational complexity because they rely on handcrafted feature extraction and relatively simple optimization procedures. Consequently, they require less memory, shorter training times, and can be effectively trained using standard CPU-based systems. However, their performance depends heavily on the quality of manually engineered features and may degrade when modelling complex nonlinear ECG patterns. In contrast, deep learning models automatically learn hierarchical feature representations directly from raw ECG signals, resulting in improved classification performance. This advantage comes at the cost of increased computational complexity, higher memory consumption, longer training times, and the need for GPU acceleration. Therefore, the selection of an ML or DL

approach involves a trade-off between computational efficiency and predictive performance, which should be considered according to the application requirements.

CHAPTER 4

RESEARCH METHODOLOGY

4.1. Introduction

In the aftermath of the COVID-19 pandemic, cardiovascular health has gained renewed global attention due to a notable rise in heart-related complications, including rare post-vaccination conditions such as Thrombosis with Thrombocytopenia Syndrome. These conditions can lead to serious outcomes like sudden cardiac arrest and arrhythmia, particularly among individuals with underlying heart conditions. Advanced diagnostic tools that can accurately and instantly detect heart function are therefore becoming more necessary. Among the various diagnostic tools, the ECG remains a vital, non-invasive clinical standard for evaluating cardiac health. However, ECG signal analysis, especially in real-world environments, faces persistent challenges such as noise contamination, most notably Power Line Interference (PLI), which hampers diagnostic accuracy and decision-making.

While DL has demonstrated substantial promise in medical image analysis and bio signal classification, its application in ECG analysis still contends with unique issues. These include high sensitivity to signal quality, limited generalisation to diverse noise conditions, and insufficient integration of denoising mechanisms into the classification pipeline. Current literature reveals several efforts to address these problems individually. For example, Kalman Filter (KF)-based denoising methods have significantly improved the SNR of ECG signals under 50 Hz and 60 Hz PLI,

By combining an attention-guided deep autoencoder-LSTM architecture with adaptive Kalman-based ECG denoising, the proposed research seeks to create an integrated, real-time arrhythmia classification system that fills these important gaps. This system is designed to operate effectively even on short-duration or single-beat ECG signals and is optimised for deployment in noisy, real-world environments, including those affected by emerging post-COVID cardiovascular risk factors. Figure 4.1 displays the overall structure of the suggested model, with each module's structural development guided by taxonomical references. Preprocessing methods, while essential to signal clarity, are deliberately discussed in a separate section later in the thesis due to their foundational importance and to maintain focus on the deep learning components within this chapter.

This chapter outlines the methodology adopted for the proposed system in a sequential and modular manner. Section 4.2 presents the research design and justifies the selected techniques. Section 4.3 explains the data collection strategies, including source datasets and pre-processing. Section 4.4 discusses the detailed architecture of the proposed deep learning model. Section 4.5 elaborates on the data analysis and performance evaluation metrics. Section 4.6 addresses the validity, reliability, and ethical considerations. Finally, Section 4.7 concludes with a summary of the methodological approach and its alignment with the research objectives.

4.2 Research Approach

Although many studies have examined ECG analysis, little is known about integrating a self-attention mechanism and DL model building into ECG signal pre-processing. This innovative approach is pivotal to precise analysis of ECG

signal abnormalities. We provide a novel self-attention-based AE algorithm in this field, which differs greatly from existing work in this domain and has three main contributions:

In the discussion in the previous portion of this thesis, applying the Tuned Kalman filter to denoise the ECG wave components from the ECG waveform.

- The application of the DL model with the newly suggested self-attention-AE method is being discussed.
- Categorising ECG signals to predict cardiac arrhythmias.
- This chapter will compare the performance of the suggested self-attention-AE algorithm methodology and the innovative TKF with that of other methods.

Pre-processing will be carried out using the suggested self-attention-AE method employing denoised ECG data with a novel TKF, which improves the clarity of the R-R peak cycle and QRS complex. Additionally, cardiac arrhythmia is identified through the classification of ECG signals. It is useful for early medical therapy to prevent potential health hazards because the categorisation result predicts different arrhythmic disorders. Most significantly, QRS complex and R-R peak analysis of the ECG waveform allow medical professionals to comprehend the condition of a single heartbeat, which otherwise behaves erratically due to a variety of patient diseases. The medical community should be encouraged by the possibility of early cardiac problem diagnosis and comprehension.

4.2.1 Theoretical Framework

This research is grounded in the interdisciplinary integration of signal processing theory and deep learning-based pattern recognition. The Kalman Filter, rooted in

linear quadratic estimation, serves as the theoretical basis for adaptive noise reduction in time-series biomedical signals, particularly ECG. For classification, the framework draws from the principles of RNNs and Autoencoders, which are effective in learning temporal dependencies and feature representations from sequential data. Integrating Self-Attention Mechanisms improves the model's ability to focus on critical signal regions, such as the QRS complex and R-R intervals, by adaptively weighting relevant input features.

This hybrid framework reflects a shift from isolated module designs (where denoising and classification are performed separately) toward a unified pipeline, capable of simultaneous noise suppression and precise heartbeat classification even under real-world constraints like PLI and signal distortion.

4.2.2 Research Design

The overall design follows a quantitative, experimental, and applied research approach. The study is structured into three sequential modules:

4.2.2.1. Signal Denoising (Pre-processing Stage)

A clear analysis of the ECG signal is necessary for cardiac arrhythmia. Among ECG signal components, the QRS complex and R-R intervals remain significant waveforms. Their timing and pattern provide valuable information about the current status of the heart and show the electrical activity of the heart during ventricular contraction. However, the ECG measurements are distorted because of PLI. The MIT-BIH Arrhythmia database is consulted during the proposed study at <https://www.physionet.org/>. There are more than 4000 ECG signal recordings in this collection [50,51]. The proposed study used the complete MIT-BIH

Arrhythmia Database, a publicly available benchmark dataset widely adopted in ECG classification research. Since the objective was to develop and evaluate a deep learning model using a standard benchmark, the sample size was predetermined by the database rather than calculated statistically. Using the complete dataset maximizes data diversity, improves model generalisation, and enables fair comparison with existing state-of-the-art methods.

The electrical sources flowing through cables and power lines cause PLI, a type of "noise" that can be heard in ECG readings. Harmonics constitute the PLI found in ECG signals. An appropriate filter has been selected to reduce harmonics, and before implementing the suggested DL model, the PLI issue must be fixed using a TKF, which achieves signal denoising when the ECG data are pre-processed.

By processing current signals iteratively, the suggested TKF provides the best possible prediction of the state of the system.

The DWT notch filter with a denoising KF, but since the TKF response provides PLI through attenuation, the KF enhances ECG signal denoising. Hence, the proposed research developed a TKF intended for denoising ECG signals, which is compared with the notch filter's performance.

The TKF module's primary objective is to reduce KF's inaccuracy to generate a denoised ECG signal that is more accurate. Lowering state estimation error is a common method to start in the KF. The error is therefore greatly reduced by concentrating on lowering state prediction error sensitivity. By lowering the squared mean and covariance trace, this sensitivity was successfully reduced as an arbitrary variable.

PLI is easily recognised as the ECG's interfering voltage, which has a frequency of 50–60 Hz. The errant impact from loops in the patient's cords could be the source of the disruption. The suggested technique cancels PLI using time-frequency non-stationary signals with a WT that works alongside the TKF processing. The analytical model for Kalman and dynamic filters is discussed in later sections. One presumes that single-tone PLI noise intrusion involves various sinusoids with erratic amplitude and phase, such as:

$$S_s = A \cos(2\pi i \times sf_m \times f_n + \theta) \quad (\text{Eq. 4.1})$$

Furthermore, Equation (Eq. 4.2) can be expressed as follows by applying trigonometric manipulation and including a model error parameter [122]:

$$S_{(s+1)} + S_{(s-1)} = 2 \cos\left(2\pi i \times \frac{f_i}{f_n}\right) S_s + \xi_s \quad (\text{Eq. 4.2})$$

As far as can be observed, PLI noise does not show any abrupt changes in amplitude or phase. A combination of PLI, pure ECG, and an unwanted signal or disturbance is known as the "pure ECG damaged by PLI noise," and it is provided by:

$$Y_s = S_s + W_s \quad (\text{Eq. 4.3})$$

Where S_s and W_s are PLI at 50, 60 Hz, and zero denotes an arbitrary span that encompasses all signals and noises other than PLI. This investigation overlooks possibilities that possibly encompass bio signals and additional disruptions because it only looks at 50 and 60 Hz PLI. PLI noise tracking becomes feasible when Eqs. 4.2 and 4.3 are converted into state-space format for the KF approach, and provided as:

$$\mathbf{X}_{(s+1)} = \mathbf{C}_x \mathbf{s} + \mathbf{C}_g \mathbf{s} \quad (\text{Eq. 4.4})$$

$$\mathbf{Y}_s = \mathbf{d}^T \mathbf{x}_s + \mathbf{v}_s \quad (\text{Eq. 4.5})$$

PLI is computed using the model on a noisy ECG signal. A mathematical procedure known as a TKF uses noisy observations of a dynamic system to ascertain its state. The prediction and update steps are the two main parts of the filter. Using the system's state transition model, the prediction phase forecasts the present state of the system based on the previous state and, if relevant, any control input.

$$\hat{\mathbf{X}}_{\bar{h}} = \mathbf{F}_h \hat{\mathbf{X}}_{h-1} + \mathbf{B}_h \mathbf{u}_h - \mathbf{1} \quad (\text{Eq. 4.6})$$

The matrix of state transitions establishes a connection between the current state and its predecessor. The error covariance matrix, which is calculated during the prediction stage, shows the uncertainty related to the estimated state, whereas the control input matrix connects the system's state to the control input:

$$\mathbf{P}_{\bar{k}} = \mathbf{F}_k \mathbf{P}(k-1) \mathbf{F}_k^T + \mathbf{Q}_k \quad (\text{Eq. 4.7})$$

The process noise covariance matrix represents the uncertainty of the state transition model. The updated state estimate and error covariance matrix are produced during the update step by combining the measurements with the projected state estimate.

$$\hat{\mathbf{X}}_h = \hat{\mathbf{X}}_{\bar{h}} + \mathbf{K}_h (\mathbf{Y}_h - \mathbf{H}_h \hat{\mathbf{X}}_{\bar{h}}) \quad (\text{Eq. 4.8})$$

Where, time h Measurement is denoted by $\mathbf{Y}_h$. Measurements and states are connected by the observation matrix. The Kalman gain matrix determines the

weights given to the measurements in the updated state estimate and the forecast state estimate. Additionally, the error covariance matrix is modified.:

$$\hat{P}_h = (I - K_h M_h) P_{\bar{k}} \quad (\text{Eq. 4.9})$$

Here I is the identity matrix. Following the definition of the dynamic model, the KF is used to calculate PLI. The following procedures are offered, and the time propagation is provided by:

$$P_s + 1 = C P_s^+ C^T + q s c c^T \quad (\text{Eq. 4.10})$$

Kalman Gain is given by:

$$H_s = \left[\frac{P^s d}{d^T P^s d + K_s} \right] \quad (\text{Eq. 4.11})$$

Measurement Propagation is given by:

$$\hat{X}_s^+ = \hat{X}_s^- + H_s [Y_s - d^T \hat{X}_s^-] \quad (\text{Eq. 4.12})$$

$$\hat{P}_s^+ = \hat{P}_s^- - H_s \hat{d}^T \hat{X}_s^- \quad (\text{Eq. 4.13})$$

The calculation and the state are connected by the observation matrix. To control the continuous prediction model, the current state receives the output from the previous state as input. In contrast to the Kalman filter state model, we employed a feedback loop in the TKF to compare QRS-complex and R-R interval peaks to confirm denoising of initial signals (including harmonics).

The filtered ECG signal is obtained by tracking the PLI and subtracting it from the noisy ECG after applying TKF. Figure 4.2 illustrates this process.

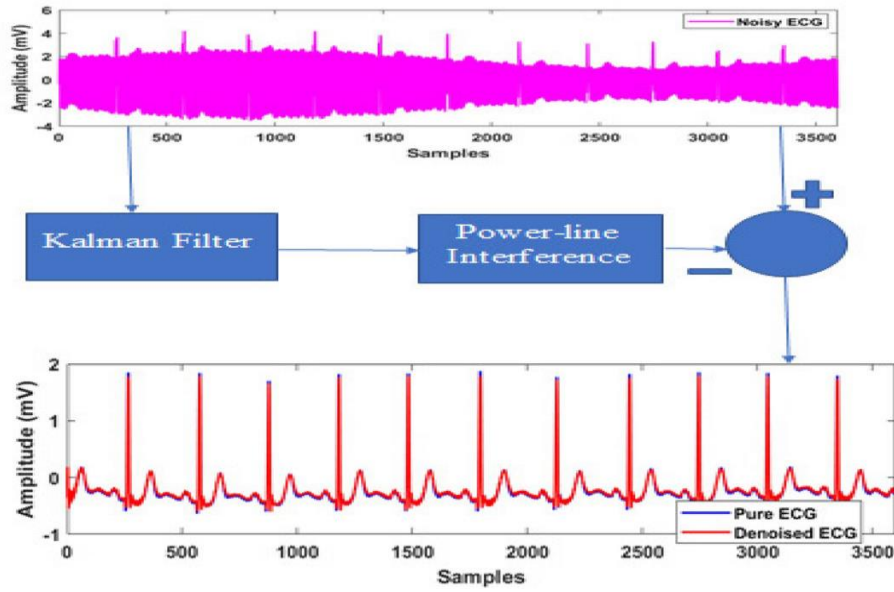


Figure 4.2: Block Diagram of 50 and 60 Hz PLI Denoising ECG using KF

A dynamic system's state space model is given as:

$$X_h = F_h X_{(h-1)} + B_h u_h + W_h \quad (\text{Eq. 4.14})$$

$$Y_h = H_h X_h + Y_h \quad (\text{Eq. 4.15})$$

Zero-mean Gaussian (ZMG) white noise with a specified covariance matrix is used to represent process noise. The measurement noise is likewise represented as ZMG white noise with its covariance matrix, and the observation matrix connects the measurement and state [52]. The KF determines the system state by predicting the current state based on the control input and prior state, then correcting it depending on the measurement. Consequently, the prediction step is provided by:

$$\hat{X}_s^- = F_h \hat{X}_h - 1 + B_h u_h \quad (\text{Eq. 4.16})$$

$$P_h^- = F_h P_h - 1 F_h^T + Q_h \quad (\text{Eq. 4.17})$$

where $\hat{X}h^-$ is the estimated anticipated state at the time h given observations over time $h - 1$. The anticipated error covariance matrix at time k is $\hat{P}h^-$, given the data up to time $h - 1$. Estimated state of the system at time $h - 1$ is represented by $\hat{X}h - 1$, given the observations up to that point. $P_h - 1$ is the estimated error covariance matrix at time $h - 1$, given data up to that point for updating, is provided by:

$$K_h = P_h^- H_h^T [(H_h P_h^- H_h^T + R_h)]^{-1} \quad (\text{Eq. 4.18})$$

$$\hat{X}_h = \hat{P}_h^- + K_h (Y_h - H_h \hat{X}_h^-) \quad (\text{Eq. 4.19})$$

$$P_h = (I - K_h H_h) P_h^- \quad (\text{Eq. 4.20})$$

Where, K_h or the Kalman gain matrix at time k , determines how much weight is given to the predicted state estimate, and the measurement is included in the updated state estimate. Given the observations up to time h , $\hat{X}h$ represents the updated state estimate at time h . P_h is the updated error covariance matrix at given time h given observations up to time k .

Given the data available up to a certain time, recursive TKF equations (4.17)–(4.20) are applied to estimate the system's state at each time step. The TKF serves as a mathematical framework for determining the state of a dynamic system from noisy observations, operating through two important stages: prediction and update. While the prediction phase uses a state transition model and control input to predict the system's current state, the update step uses a measurement and observation matrix to update the estimation of the state and error covariance matrix and correct the prediction [53].

Based on the model of detected current system state is then fed into the state of the following system. The state is regarded as the prediction state during the first filter iteration, and the filter iteration variance feedback is used to apply the anticipated outputs to achieve the current state estimate. The current state prediction graph using TKF is displayed in Figure 4.3.

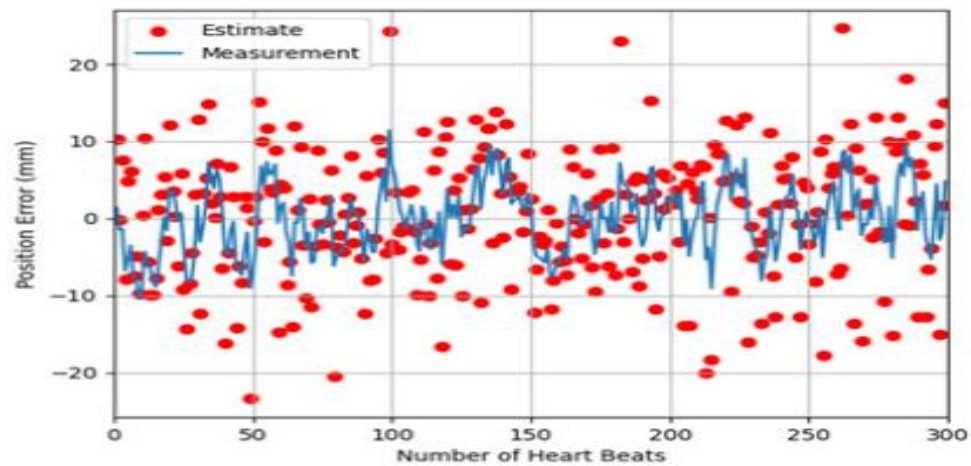


Figure 4.3: Current State Prediction With The Tune Kalman Filter

Based on the system's dynamic model, the prediction process extrapolates the present system state estimate and its variation to the following system state.

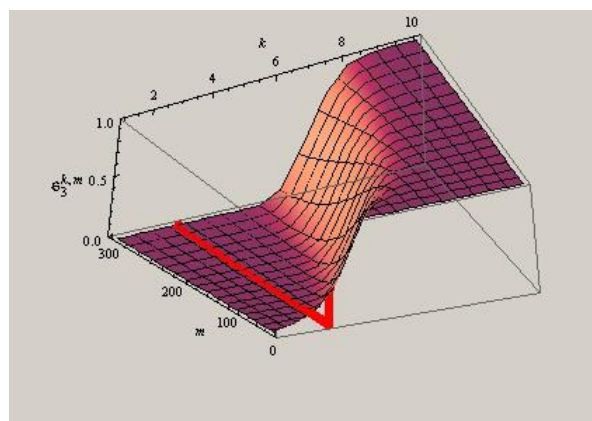


Figure 4.4: Current State Estimate of The Tuned Kalman Filter

Figure 4.4 shows the current state of estimation of TKF, in which initialisation is regarded as the Predicted State Estimate and Variance at the first filter iteration. The following filter iterations use the prediction results as the Predicted State Estimate and Variance

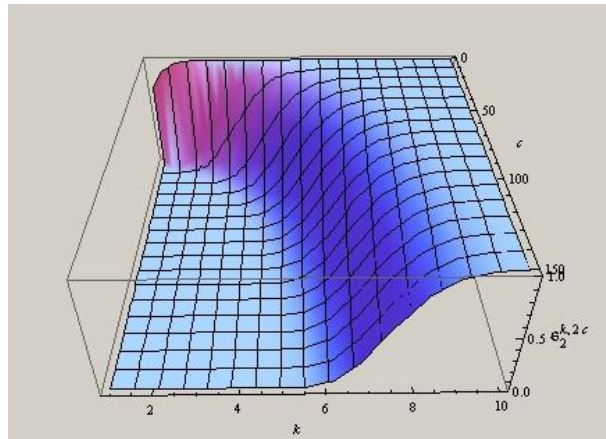


Figure 4.5: Predicted State Estimate of Tuned Kalman filter

As a result, power line interference reduces interference from ECG signals since the TKF is an ideal state predictor that efficiently filters out noise. Figure 4.5 indicates the Predicted State Estimate of TKF, where TKF increases SNR and enhances the quality of the ECG signal by identifying the signal's present state. Furthermore, the denoising effectiveness of TKF is extremely reliant on fine-tuning of its variables, such as measurement and noise covariance matrices. Better decisions and fine-tuning are carried out to accomplish optimal denoising capabilities. Moreover, the functionality of the TKF can easily be improved by including supplemental signal processing approaches, such as wavelet decomposition, to reinforce the filter's efficiency.

4.2.2.2 Arrhythmia Classification (Deep Learning Stage)

The self-attention mechanism has gained significant traction across various domains due to its adaptability, proving highly effective in applications such as

speech processing, emotion recognition, phoneme identification, and neural machine translation. In the medical field, particularly in cardiovascular analysis, self-attention models offer promising advancements in automating and enhancing diagnostic accuracy. Deep learning classification methods, combined with self-attention, can streamline echocardiography interpretation by segmenting images into specific orientations and structures, and can be equally powerful in ECG signal analysis [54]. Specifically, arrhythmia detection benefits from denoising ECG signals during preprocessing, followed by accurate classification of individual heartbeats based on QRS-complex and R-R peak identification. Self-attention–based autoencoder (AE) systems are increasingly being adopted for such tasks, offering automated, real-time analysis of cardiovascular data and improving patient management. These systems can efficiently extract relevant features from digital health records, identify high-risk phenotypes using natural language processing, and support early detection of conditions like atrial fibrillation, exemplified by FDA-approved tools such as AliveCor’s Kardia. Moreover, one-dimensional self-attention CNN architectures integrated with WT further accelerate the preprocessing and classification pipeline, making them ideal candidates for robust, high-speed ECG analysis and decision support in clinical settings [57]. Building upon these advancements, a Self-Attention Autoencoder model is developed in this research to simultaneously learn spatial (morphological) and temporal (rhythmic) features of ECG signals. This model is specifically designed to handle single-beat and short-duration ECG classification tasks, thereby enhancing early detection capabilities. However, traditional classifiers such as LR, SVM, XGBoost, and DTs often fall short in performance. To overcome these limitations, we introduce a novel algorithm named AI-DenseFit, which employs the Adam optimiser for

dynamic hyperparameter tuning. The architecture consists of densely connected layers where outputs are reused in a feedback loop to refine learning progressively. In this setup, the output of each layer contributes not only to the subsequent layer but also loops back to influence earlier computations, enabling the Adam optimiser to fine-tune weights and parameters across the network iteratively. This structure significantly boosts the learning capacity and accuracy of the model. The experimental flow of this architecture is shown in Figures 4.6 and 4.7, illustrating the detailed line of action for executing the proposed model [58]. Here, RNN / LSTM (Self-Attention-AI) uses Recurrent Neural Networks and Long Short-Term Memory units enhanced with self-attention to capture both temporal dependencies and important features from the input signal P (e.g., ECG data). Self-attention improves focus on relevant points in the sequence. Then, Kalman Filter Denoising and Classification applies a Kalman filter to reduce noise while preserving key waveform components. Also performs classification of the processed signal into specific arrhythmia or normal categories. Encoder compresses the input P into a lower-dimensional representation Q by extracting key features and discarding redundant information. Latent Representation (Q) represents the compact, encoded version of the input, capturing the most informative aspects for reconstruction and analysis. The decoder reconstructs the original signal P' from the encoded representation Q , ideally retaining important patterns while removing noise. The autoencoder equation ($AE = \text{Decoder}(\text{Encoder}(P))$) shows the mathematical relationship for reconstruction: the autoencoder output P' is obtained by decoding the encoded version of P .

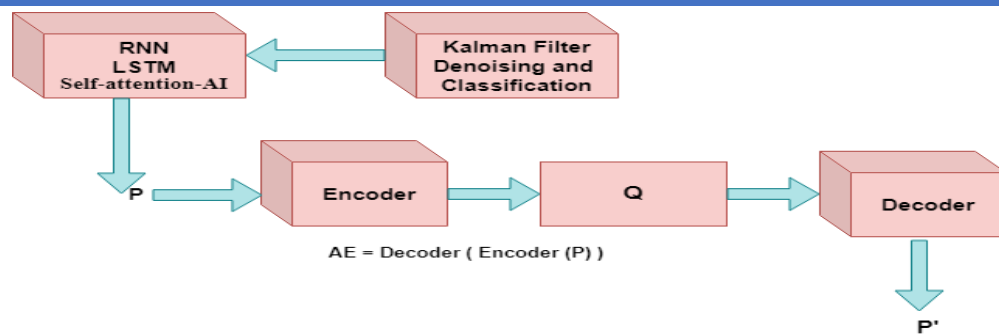


Figure 4.6: Proposed Model Component Architecture

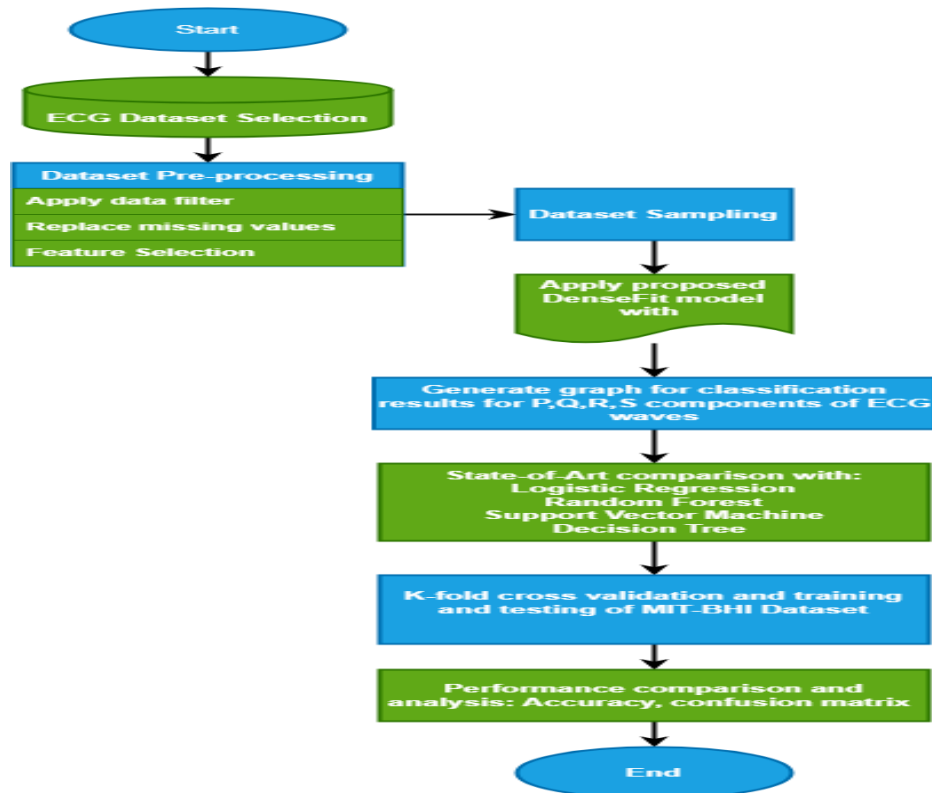


Figure 4.7: Proposed Methodology Flow

Here is the explanation of the Proposed Methodology Flow. When we start the process, we begin with an initial Block of state: Start – Initiates the ECG signal classification workflow. ECG Dataset Selection – Chooses the ECG dataset for analysis. Dataset Pre-processing – Cleans and prepares the dataset by filtering noise, handling missing values, and selecting relevant features. Dataset Sampling – Extracts

representative data samples for training and testing. Apply proposed Dense Fit model

Uses the designed Dense Fit model to process and classify ECG data. Generate graph for classification results. Plots classification outcomes for P, Q, R, and S components of ECG waves. State-of-the-art comparison – Compares results against traditional ML models such as Logistic Regression, Random Forest, SVM, and Decision Tree. K-fold cross-validation and testing – Evaluates model robustness using repeated training/testing on the MIT-BHI dataset. Performance comparison and analysis – Assesses accuracy and confusion matrix results, and at the end, we stop the process.

Further, we modified the 'AI-Dense Fit' model for performance optimisation to improve the classification accuracy, and to achieve high accuracy, we developed the 'Self-attention-AE Model'. The 'Self-attention-AE' model is shown in Figure 4.8.

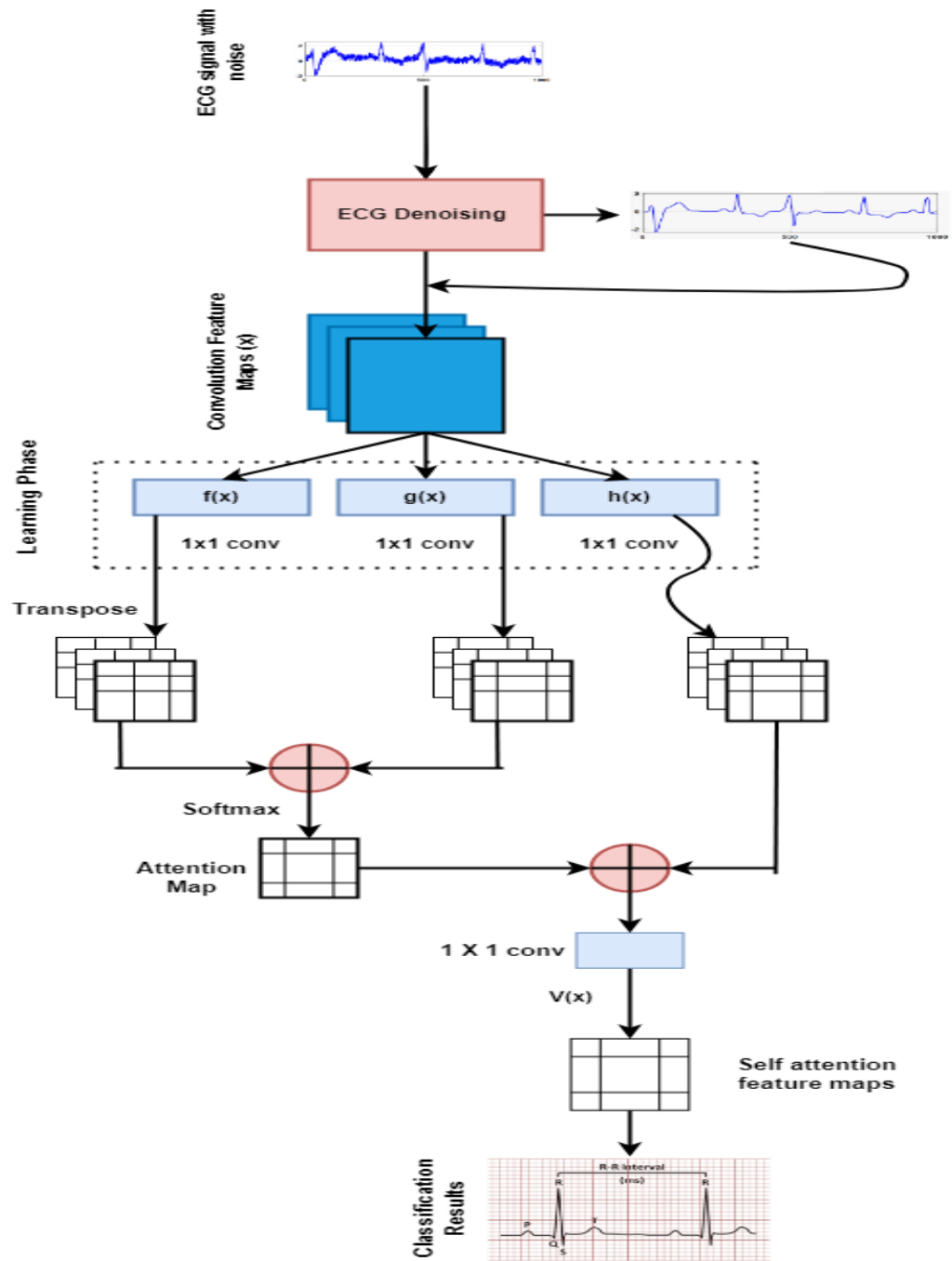


Figure 4.8: Proposed Self-attention-AE Model

The suggested technique of splitting the MIT-BIH dataset into two sets, training and testing used to pre-process the data. Further, an arbitrary random division is applied to the entire dataset. The following is the pseudo-code for executing the proposed Self-attention-AE Model.

The Self-attention-AE method, which encodes and decodes data to reduce reconstruction errors, and the LSTM worked together in the suggested system to increase the accuracy of CVD prediction. To confirm the improved accuracy, various threshold values, training, and validation processes are repeated. Variance between P and P' is minimised by training the suggested model to reduce the reconstruction loss. For real-value inputs, reconstruction losses are calculated using Mean Squared Error (MSE) [119], where MSE is the minimum standard error. Because Q typically has a lower dimensionality than P , autoencoders are sometimes known as bottleneck neural networks. Through repeated training and validation, the Self-attention-AE algorithm removes this block in the suggested system. Finally, a comparison with the outcomes of the current system is made to assess the entire self-attention-based system.

Following the pre-processing of the ECG data, the components of the signal are classified using the suggested procedure. Following pre-processing and denoising, we used the suggested algorithm to categorise the components of the ECG waveform.

Proposed algorithm pseudo code: AI-DenseFit Model

Input: MIT-BIH arrhythmia database

Dataset pre-processing and filtering, sampling, and feature selection of dataset entries

Identification of P, Q, R, S, and T-peaks of ECG

Record the peak of P, T wave, and QRS complex with a graph

For all the ECG datasets

Apply the 'AI-DenseFit' model

Adjust Max-pooling, Softmax, and ReLU filters with appropriate K-fold and epoch size

Execute feature extraction

Conduct 'AI-DenseFit' model training and testing

The AI-DenseFit was further compared for precision, recall, and accuracy parameters with other algorithms like LR, SVM, XGBoost, and DT. Based on the execution of the 'AI-DenseFit' model, we compiled results with a 5 k-fold and epoch size for optimum results obtained with epoch size 75. Further, for performance optimisation, we developed a Self-attention-AE Model, which can improve the accuracy of classification, and attention-based systems can be an automated solution for cardiac arrhythmia classification.

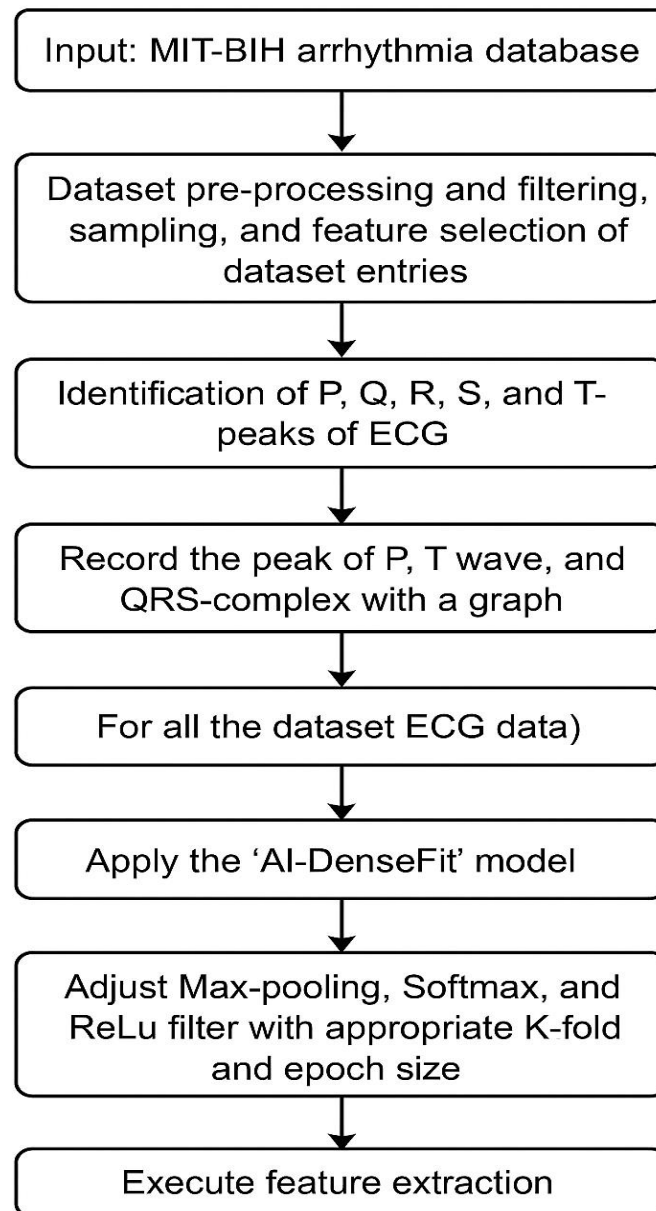


Figure 4.9 Flow of the Pseudo Code of AI-Dense Fit

Proposed algorithm pseudo code: Self-attention-AE Model

Input: MIT-BIH arrhythmia database

Dataset pre-processing and filtering, sampling, and feature selection of dataset entries

Identification of P, Q, R, S, and T-peaks of ECG

Record the peak of P, T wave, and QRS complex with a graph

For the ECG data

Apply the LSTM model

Adjust Max-pooling, Softmax, and ReLU filters with appropriate K-fold and epoch size

Execute feature extraction

int Sequence Length #identify the sequence length of the data

for i in range (0, SequenceLength):

if this is the initial step

Initialise Sequence Length

else:

Sequence Length++ # increment the sequence position

Now, collaborate RNN with LSTM

Apply sigmoid function (output will be binary 0 or 1)

Sigmoid function will help to decide at the end of the sequence

Initiate the autoencoder module

Execute single-dimensional convolution autoencoder #for ECG time series data

Execute training and validation

Record: Total model loss, Classification Error, Reconstruction Error and accuracy for ECG time series signals

Display a confusion matrix

End

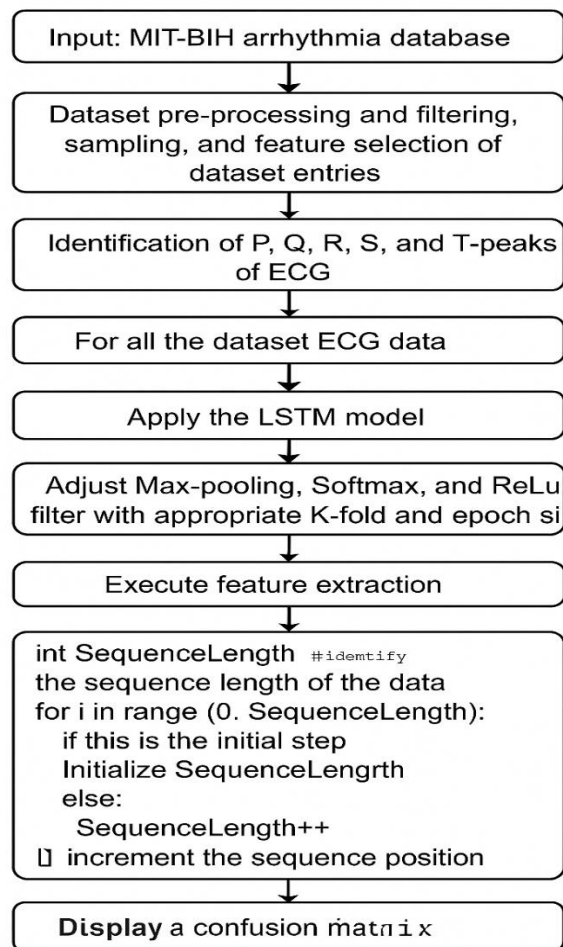


Figure 4.10: Flow of the Pseudo Code of *Self-attention-AE Model*

Performance metrics are compared between the Self-attention-AE Auto Encoder model and current algorithms. To ensure the robustness of our model, we implemented the suggested "Self-attention-AE model" using a careful application of Keras and TensorFlow (as a backend). With Python 3.11, Anaconda-3 is a reliable platform that is used to implement the suggested model. This has made it possible to securely produce classification results and confusion matrix graphs

using Tensor Board. An Intel Core i5-7400 CPU, an NVIDIA graphics card, 8GB of RAM, and 8GB of memory were used to experiment. The pre-processed dataset is split into training and testing sets by a random split technique.

In this novel, the Self-attention-AE Model is introduced to enhance the classification accuracy, which comprises an encoder and decoder for signal processing. The encoder module features four 1-D LSTM convolutional layers, whereas the decoder module includes a 1-D deconvolution (Deconv) layer. The network takes in a noisy ECG signal and, through using a TKF, produces a denoised ECG signal. Feature maps are extracted using LSTM convolutional layers, and down-sampling is achieved using a max-pooling layer of two, suppressing noise during the encoding phase efficiently.

The methodological choices presented in this chapter are directly aligned with the overarching research objective of developing a unified, adaptive, and accurate arrhythmia detection framework suitable for deployment in noisy, real-world environments. By addressing key limitations in existing literature, such as the lack of end-to-end integration between denoising and classification, sensitivity to power line interference, and the challenge of classifying short-duration signals, this work fills an important research gap. The integration of TKF with attention-guided deep learning not only enhances diagnostic precision but lays the foundation for future implementation in wearable and edge-computing cardiac monitoring systems. This is particularly relevant in the post-COVID healthcare context, where evolving cardiovascular risk profiles necessitate early, efficient, and intelligent detection strategies.

4.3 Dataset Imbalance Handling :

The MIT-BIH Arrhythmia database exhibits an inherently imbalanced class distribution, where normal heartbeats are significantly more frequent than several abnormal arrhythmia categories. Such imbalance can bias deep learning models toward majority classes, leading to reduced sensitivity for clinically important minority arrhythmias.

To minimize this problem, the class distribution was analysed before model training. The dataset was randomly divided into training and testing subsets while preserving the original class proportions through stratified sampling. During model training, batches were generated to ensure representative samples from all classes. Performance evaluation was not based solely on overall accuracy; additional metrics including precision, recall, F1-score, specificity, and confusion matrix analysis were employed to assess classifier performance across both majority and minority classes.

Furthermore, K-fold cross-validation was adopted to reduce sampling bias and improve the robustness of the proposed model. This strategy ensured that each heartbeat class participated in both training and validation across different folds, thereby improving the generalisation capability of the proposed Self-Attention-AE model.

Although the MIT-BIH Arrhythmia database exhibits class imbalance, no explicit oversampling or undersampling technique was applied. Instead, model robustness was enhanced through random sampling, repeated K-fold cross-validation, and evaluation using class-wise performance metrics such as precision, recall, F1-score, and a confusion matrix. These measures provide a more reliable assessment than overall accuracy alone and reduce the risk of misleading performance due to class imbalance.

4.4 Experimental Setup and Model Training: Here, we describe the experimental setup to explain the model training

1) Train-Test Split: The MIT-BIH Arrhythmia Database was randomly divided into training and testing subsets using an **80:20 ratio**. Eighty per cent of the ECG records were used for model training, while the remaining twenty per cent were reserved for independent testing. Randomisation was performed using a fixed random seed to ensure reproducibility.

2) Validation Strategy

K-fold cross-validation is a statistical validation technique used to evaluate how well a machine learning model generalises to unseen data. Instead of splitting the dataset only once into training and testing sets, the dataset is divided into K equal-sized subsets (folds).

The model is trained and validated K times, where:

- One-fold is used as the validation set.
- The remaining $K-1$ folds are used for training.
- This process repeats until every fold has served once as the validation set.

Medical datasets such as the MIT-BIH Arrhythmia Database are relatively limited in size.

In 5-fold cross-validation:

- 80% of the data is used for training.
- 20% is used for validation.

Since every sample is eventually used for validation, almost all available ECG data contributes to both training and evaluation.

3) Hyperparameter Tuning: This is probably the biggest missing component.

Table 4.1: Hyperparameter Tuning

Hyperparameter	Value
Learning Rate	0.001
Batch Size	32
Epochs	75
Optimizer	Adam
Activation	ReLU
Output Activation	Softmax
Dropout	0.5
Loss Function	Categorical Cross-Entropy

Hyperparameters were selected through empirical tuning. Multiple combinations of learning rate, batch size and epoch numbers were evaluated using validation accuracy. The final configuration produced the highest validation accuracy while avoiding overfitting.

4) Optimiser Settings: The network was trained using the Adam optimizer with an initial learning rate of 0.001, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-8}$, and default TensorFlow momentum parameters. Methodology lacks sufficient reproducibility details, including train-test split, validation strategy, hyperparameter tuning, and optimizer settings.

4.5 Feature Extraction Methodology:

Proposed Feature Extraction Methodology: The proposed framework performs automatic feature extraction instead of relying on manually engineered ECG features. Following ECG signal denoising using the Tuned Kalman Filter (TKF), the denoised ECG signals are provided as input to the Self-Attention Autoencoder

network. Initially, the encoder compresses the ECG waveform into a latent representation while preserving important morphological information. During this stage, convolutional operations and LSTM units learn representative characteristics including:

- P-wave morphology
- QRS complex shape
- R-wave amplitude
- RR interval variation
- ST-segment characteristics
- Temporal heartbeat sequence
- Local waveform morphology
- Long-term cardiac rhythm dependencies

The encoder transforms the input signal

$$X = \{x_1, x_2, \dots, x_n\}$$

into a compact latent feature vector

$$Z = f_{Encoder}(X)$$

where

- X denotes the denoised ECG signal,
- Z represents the learned latent features.

Instead of manually measuring ECG characteristics, the encoder automatically learns discriminative representations by minimising reconstruction loss.

Subsequently, the LSTM layer captures temporal dependencies among consecutive heartbeats.

The hidden state is computed as

$$h_t = LSTM(x_t, h_{t-1})$$

where

- x_t is the current heartbeat,
- h_{t-1} is the previous hidden state.

This enables the network to learn rhythm abnormalities that occur over time.

To further improve representation learning, a self-attention mechanism assigns higher importance to clinically significant ECG regions, especially the QRS complex and abnormal RR intervals.

The attention weights are computed as

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where

- Q = Query matrix
- K = Key matrix
- V = Value matrix

The attention mechanism allows the model to focus on diagnostically relevant waveform segments while suppressing redundant information.

The final feature vector is generated by concatenating

- latent encoder features,
- temporal LSTM features,
- attention-weighted features.

These discriminative features are then supplied to the Dense Fit classifier for arrhythmia prediction.

Unlike traditional machine learning approaches that require handcrafted feature engineering, the proposed deep learning framework automatically learns hierarchical

spatial and temporal representations directly from ECG signals, thereby improving robustness under noisy conditions and enhancing classification accuracy.

4.6 Chapter Summary

This chapter outlines a comprehensive research methodology developed to address the challenges of real-time, accurate arrhythmia detection from ECG signals, particularly in the post-COVID era, where cardiovascular complications are increasingly prevalent. The study recognises key limitations in current ECG analysis systems—namely, the disjoint treatment of signal denoising and classification, poor generalisation in the presence of noise, and inefficacy with short-duration signals. To bridge these gaps, the proposed approach integrates a Tuned Kalman filter to denoise ECG signals contaminated by Power Line Interference (PLI) and a Self-Attention Autoencoder deep learning architecture for arrhythmia classification. The methodology is structured into signal pre-processing, feature extraction, model training, and validation phases, using the MIT-BIH Arrhythmia Database as the primary data source. The TKF-based denoising approach outperforms traditional filters by adaptively removing 50/60 Hz interference while preserving critical ECG features such as QRS complex and R-R intervals. On the classification front, the Self-Attention Autoencoder model enhances learning by capturing both spatial and temporal dependencies and is further optimised through an AI-Dense Fit algorithm using the Adam optimiser. The chapter also details theoretical foundations, implementation steps, algorithmic pseudocode, and performance evaluation metrics. Ultimately, this unified framework demonstrates significant potential for deployment in real-time and resource-constrained environments such as wearable and edge-based

cardiac monitoring systems, offering a robust solution to emerging cardiovascular diagnostic needs in a post-pandemic world.

CHAPTER 5

IMPLEMENTATION AND EXPERIMENTAL SETUP

This chapter presents the detailed implementation strategy and experimental setup adopted on the road to evaluating the performance of the proposed arrhythmia classification framework. Building upon the methodological design outlined in Chapter 4, this chapter translates the theoretical architecture into a practical, executable pipeline that supports real-time and high-accuracy classification of ECG signals. The core components of this chapter include data collection, system implementation, parameter tuning, and experimental configuration for model training and testing.

5.1 Data Collection

ECG data were collected from the MIT-BIH Arrhythmia Database and clinically acquired patient records under ethical approval for model training and evaluation.

5.1.1. Participants / Materials

This study utilises two primary sources of ECG data:

MIT-BIH Arrhythmia Database (Public Dataset): A benchmark dataset sourced from PhysioNet, the MIT-BIH Arrhythmia Database contains annotated ECG recordings sampled at 360 Hz. It includes over 116,000 annotated heartbeats across 48 records from 47 patients, covering a wide range of arrhythmia types, including

ventricular and supraventricular ectopic beats, atrial fibrillation, and normal rhythms. Each record contains two channels of ECG data: lead II and lead V1 [122].

5.1.2 Sampling Strategy

MIT-BIH Dataset: Data were sampled from all 48 records, but only normal and arrhythmic beats with clear QRS morphology were retained. Signals with excessive artifacts or missing annotations were excluded. Random sampling with stratification ensured class balance for training and testing (e.g., maintaining proportions across different arrhythmia types).

5.1.3 Data Collection Methods by MIT BIH Data Set

For the MIT-BIH Dataset, ECG records were downloaded directly from the PhysioNet repository. Each signal was pre-processed (resampled, normalised, and denoised) and segmented into fixed-length windows around each R-peak for single-beat classification. Annotations were used for supervised learning.

5.1.3.1 Data Collection Methods by Real-Time Data Set

The real-time ECG data used in this study were collected from Bhatkar Hospital, located in Amravati, Maharashtra, during the period between 2023 and 2024. Data acquisition was conducted using a 12-lead ECG machine interfaced with the Simul-G software, enabling digital extraction of ECG signals. The dataset comprises clinical ECG recordings from 400 patients, spanning an age group of 28 to 60 years. Among the participants, 200 were male, and 200 were female, ensuring a balanced gender representation. Each ECG signal corresponds to one of five beat categories relevant to cardiac arrhythmia classification. The distribution includes

20 Normal (N) beats, 80 Supraventricular (S) ectopic beats, 147 Ventricular (V) ectopic beats, 111 Fusion (F) beats, and 42 Unknown (Q) beats. The ECG signals were sampled and pre-processed in digital form as provided by the hospital infrastructure. All recordings reflect real-time physiological data, ensuring high clinical relevance and diagnostic variability.

5.1.4 Instrumentation

- **Software Platforms:**

- **TensorFlow:** For training deep learning models.
- **Python:** For implementing and testing Kalman filtering.
- **Anaconda (Python 3.11):** Used as the main development environment.
- **TensorBoard:** For visualising training metrics and confusion matrices.

5.2. Data Analysis

The ECG data utilised in this research, sourced from both the MIT-BIH Arrhythmia Database and clinically collected patient reports, underwent a systematic preparation process before analysis. Initially, the raw ECG signals were segmented into fixed-length windows centred around the R-peaks, which were accurately detected using the Pan-Tompkins peak detection algorithm. Each extracted segment encompassed the key morphological components of the ECG waveform, including the P-wave, QRS complex, and T-wave, which are essential for reliable arrhythmia classification. To improve signal quality, a TKF was applied for denoising, effectively suppressing power line interference at 50/60 Hz and enhancing the clarity of QRS complexes. Subsequently, all segments were

normalised using min-max scaling to a uniform amplitude range (0 to 1 or 10 to 1, depending on the dataset), ensuring consistency for deep learning model input [75]. Each segment was then labelled based on the corresponding annotations provided in the MIT-BIH dataset, identifying classes such as Normal, Premature Ventricular Contraction (PVC), Atrial Premature Beat (APB), and Left Bundle Branch Block (LBBB), while ambiguous or overlapping labels were excluded to maintain training integrity. Finally, the dataset was divided into training and testing sets using an 80:20 split, with stratified K-Fold cross-validation applied to preserve class balance and ensure that each fold proportionally represented all arrhythmia types during model evaluation [123].

5.2.1. Analysis Techniques

Two primary layers of analysis were carried out:

5.2.1.1. Denoising Evaluation (Signal-Level Analysis):

The performance of the proposed signal preprocessing and classification pipeline was assessed through both quantitative evaluation and qualitative visualisation techniques. For the quantitative assessment, key metrics such as classification error, reconstruction error, precision, and recall were computed to evaluate the effectiveness of the TKF in comparison to the baseline notch filter. The results were organised into comparative tables, clearly demonstrating the superiority of TKF in preserving diagnostically relevant ECG waveform characteristics, particularly under high noise conditions. In addition to numerical evaluation, qualitative visualisation was employed by plotting ECG waveforms before and after the application of filtering techniques. These visualisations highlighted the TKF's ability to effectively suppress power line interference while maintaining the

structural integrity of critical features such as the R-R intervals and QRS complexes, which are essential for accurate arrhythmia classification [120]

5.2.1.2. Arrhythmia Classification (Model-Level Analysis):

- **Model Training and Testing:**

- The Self-Attention Autoencoder model was trained on pre-processed data using categorical cross-entropy loss and Adam optimiser.
- The model's performance was compared against existing classifiers.

- **Performance Metrics:**

Standard evaluation metrics were calculated:

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

$$\text{Precision} = \frac{TP}{(TP + FP)}$$

$$\text{Recall (Sensitivity)} = \frac{TP}{(TP + FN)}$$

$$\text{F1-Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})}$$

- A Confusion Matrix was used to assess model performance across different arrhythmia classes.
- Reconstruction Loss was used to quantify the reconstruction error of the autoencoder, indicating how well the model learned latent ECG representations.

5.2.2.3 Software and Tools

The following software platforms and tools were used during the analysis phase:

- **Python Programming Environment:**
- **TensorFlow 2.x + Keras:** For model design, training, and evaluation.
- **Scikit-learn:** For baseline machine learning classifiers and metric evaluation.
- **WFDB Toolkit:** For loading and visualising ECG data from MIT-BIH.
- **Matplotlib & Seaborn:** For visualisation of confusion matrices, signal graphs, and error plots.
- **Anaconda (Python 3.11):** Main development environment.
- **TensorBoard:** Used to monitor training performance, visualise loss trends, and inspect model outputs.
- **Hardware Configuration:**
- Intel Core i5-7400 CPU, 8GB RAM, NVIDIA GPU (CUDA-enabled) for accelerated deep learning training.

5.3 Deep Learning Model Parameter Settings:

Table 5.1: Model Parameter Values

Parameter	Value
Optimizer	Adam
Learning rate	0.001
Batch size	32
Number of epochs	100
Loss function	Categorical Cross-Entropy
Activation (Encoder)	ReLU
Output activation	Softmax
LSTM units	128
Dropout	0.5
Latent dimension	64
Early stopping	Patience = 10
Validation split	20%
Weight initialization	Glorot Uniform
Framework	TensorFlow 2.x with Keras

5.4. Validity and Reliability

5.4.1 Measures Taken

To ensure the validity and reliability of the research findings, the following steps were systematically implemented:

- **Cross-Validation:** A 10-fold stratified cross-validation technique was employed to train and validate the proposed Self-Attention Autoencoder model. This ensured that each arrhythmia class was proportionally represented in both training and validation sets, enhancing the generalizability and robustness of the model.
- **Benchmark Dataset (MIT-BIH):** MIT-BIH Arrhythmia Database, a globally recognised and extensively validated dataset, was used for training and testing. Its

diverse set of labelled ECG signals covering multiple arrhythmia classes contributes to construct validity.

- **Ground Truth Verification:** Classification labels were verified against expert annotations available in the dataset, ensuring labelling accuracy and reducing human-induced variability.
- **Repeated Training and Evaluation:** The deep learning model was trained across multiple epochs and with different random seeds. The results were averaged to reduce the impact of initialisation biases and outliers, improving internal reliability.
- **Signal Quality Assurance:** Preprocessing using the Tuned Kalman filter ensured that denoising was applied consistently across all ECG signals, thereby reducing the impact of external noise and improving measurement reliability.
- **Performance Metrics:** A comprehensive evaluation using multiple metrics, including accuracy, precision, recall, F1-score, confusion matrix, and reconstruction loss, provided a multi-perspective validation of model performance.

5.4.2 Limitations

Despite the rigour and effectiveness of the proposed methodology, several limitations are acknowledged. Firstly, the model's performance has been evaluated using the MIT-BIH Arrhythmia Database, which may limit its generalizability to real-world ECG signals collected from different demographics, electrode placements, device resolutions, or clinical environments. Secondly, although the system is architected for real-time applications in wearable or edge-computing scenarios, full deployment and testing on embedded platforms were not performed due to hardware and resource constraints. Thirdly, the model exhibits a dependence

on precise signal segmentation, particularly on accurate R-peak detection. Any errors during segmentation, especially under conditions involving motion artifacts or noise, can propagate through the classification pipeline and impact overall accuracy. Lastly, while the model demonstrates strong performance on publicly available datasets and partially collected clinical data, comprehensive clinical validation involving expert cardiologist review is still pending. This step is crucial to ensure the model's reliability, safety, and applicability in real-world healthcare settings before implementation.

5.4.3 Justification of Chosen Methods

The methodology adopted in this study is justified based on its alignment with research objectives and the nature of the problem:

- TKF offers a mathematically robust and adaptive solution to real-time denoising of ECG signals contaminated by 50/60 Hz power line interference, making it more effective than traditional filters for PLI suppression.
- The Self-Attention Autoencoder model combines the temporal modelling power of recurrent networks with the selective feature enhancement of attention mechanisms. This makes it particularly suitable for single-beat or short-duration ECG classification under noisy conditions.
- Using the MIT-BIH Arrhythmia Dataset, a gold-standard dataset in cardiac research, adds credibility and enables direct comparison with existing approaches.
- The evaluation framework based on cross-validation, statistical metrics, and visualisation tools ensures repeatability, reliability, and transparency in performance reporting.

Collectively, these methods are well-suited to achieving the goal of building a unified, accurate, and real-time arrhythmia classification system capable of functioning in practical, noisy environments.

5.5 Ethical Considerations

Throughout this research, ethical guidelines were strictly adhered to, ensuring respect for the rights, privacy, and well-being of all participants involved. The research complies with standard ethical protocols for biomedical data handling and human subject interaction, as outlined here:

- **Informed Consent:** For the clinical portion of the study involving OM-chanting participants, informed written consent was obtained from all individuals before participation. Participants received comprehensive information about the study's objectives, methods, possible risks and rewards, and their freedom to discontinue participation at any moment without facing any repercussions.
- **Confidentiality:** All personal identifiers and health information of participants were anonymised. Patient data collected from ECG reports were assigned unique codes, and any link between identity and data was securely stored in an encrypted, access-controlled system. Only authorised personnel involved in the study had access to this mapping.
- **Anonymity:** The data used for analysis, including ECG recordings and questionnaire responses, were de-identified before processing and reporting. No names, personal identifiers, or specific details that could trace back to individual participants were included in the dataset or any published findings.

- **Compliance with Standards:** Declaration of Helsinki's ethical principles and the Indian Council of Medical Research's (ICMR) criteria for biomedical research involving human subjects were followed in the research. Ethical approval was sought from a local ethics committee where applicable.
- **Data Security and Integrity:** All data, including the MIT-BIH dataset and clinical ECG recordings, were stored on password-protected systems with encrypted backups. Data analysis was performed in secure environments to ensure data integrity and prevent unauthorised access.

By ensuring voluntary participation, confidentiality, and secure data handling, the research upheld high ethical standards throughout its execution.

5.6 Chapter Summary:

This chapter details the practical implementation and experimental framework used to validate the proposed arrhythmia classification system. Leveraging the methodology from the previous chapter, it outlines how ECG signals—sourced from the MIT-BIH Arrhythmia Database and clinical data—were collected, pre-processed, and analysed for real-time classification. A tuned Kalman filter was employed for denoising power line interference, followed by segmentation and normalisation of ECG signals for model input. The Self-Attention Autoencoder model was implemented using TensorFlow and trained using cross-validated data to ensure balanced class representation. Comprehensive evaluation was conducted using metrics such as accuracy, precision, recall, F1-score, confusion matrix, and reconstruction loss, comparing the proposed model's performance to traditional classifiers. Visualisations confirmed TKF's superior denoising capability, and classification outcomes demonstrated high accuracy on short-duration ECG

signals. Validity and reliability were strengthened through stratified 10-fold cross-validation, repeated runs, and use of expert-annotated benchmark datasets. Ethical standards, including informed consent, anonymisation, and secure data handling, were strictly followed throughout the study. Despite some limitations, such as a lack of full real-time deployment and dependence on accurate R-peak detection, the chapter confirms the system's readiness for future applications in edge-based or wearable cardiac monitoring devices.

CHAPTER 6

RESULTS AND PERFORMANCE EVALUATION

This chapter presents a comprehensive analysis of the experimental results obtained from implementing the proposed arrhythmia classification framework. It evaluates the system's effectiveness in terms of signal denoising, heartbeat classification accuracy, and real-time applicability across both benchmark and clinical ECG datasets.

6.1. Evaluation of ECG Denoising under 60 Hz PLI

By calculating output SNR and analysing the reconstructed ECG signal following denoising, the efficacy of ECG filtering is assessed quantitatively and qualitatively. The following figures provide a visual representation of the noise reduction technique's impact. Figure 6.1 shows a clean ECG, while Figure 6.2 shows a noisy signal.

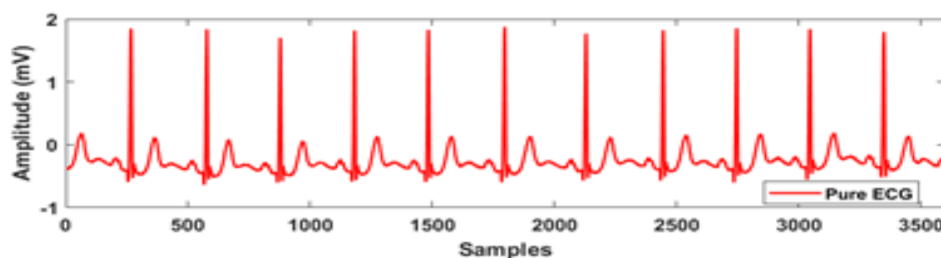


Figure 6.1: Clean ECG

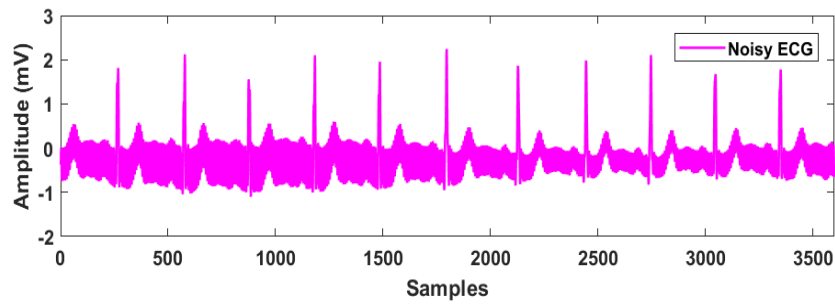


Figure 6.2: Noisy 60 Hz ECG Input to the System

The ECG record of Pid 100 at 15dB input SNR was combined with 60 Hz PLI noise to create a noisy ECG signal. Figures 6.3 and 6.4 display the whole set of filtered results.

Although the notch filter is an effective denoising technique, it is observed that for some samples, the amplitude of R-peaks decreases when SNR is low.

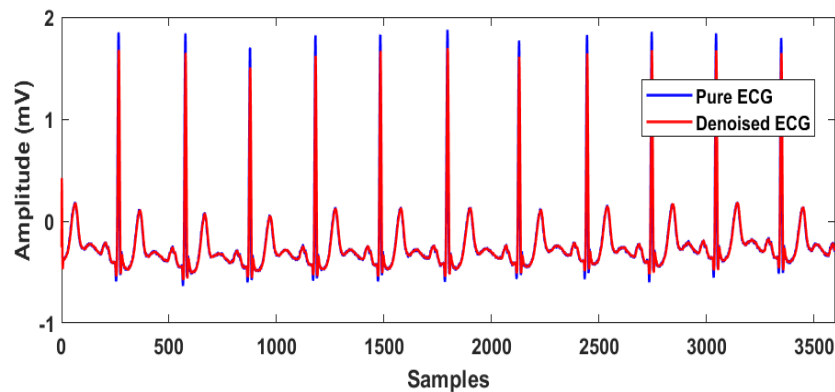


Figure 6.3: 60 Hz Denoising Results for ECG Notch Filter

It can be seen in Figure 6.3 that the suggested method successfully removes 60Hz PLI noise from ECG and closely follows the shape of the ECG signal. The results obtained after denoising indicate that this technique outperforms the notch filter in terms of preserving ECG diagnostic information. To better understand this result, a quantitative analysis of the output SNR values for each strategy was conducted.

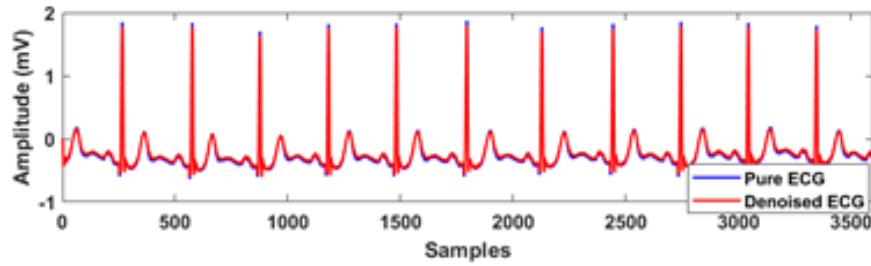


Figure 6.4: Proposed 60 Hz Removal Denoising Results for ECG 100 at 15 dB

Table 6.1 makes it clear that the approaches considered yield a lower output SNR than the suggested approach.

Table 6.1: Denoising Results with 60 Hz of Kalman Filter

Input SNR	Pid-100	Pid-110
-15 dB.	20.09	23.05
-20 dB.	20.39	23.20
-25 dB.	19.98	23.02
-30 dB.	19.43	22.14

Comparatively, KF has an -20 dB SNR of 23.20 dB at the output, whereas the notch filter has an SNR of 17.85 dB at the output. The higher output SNR achieved by the Kalman Filter demonstrates its ability to estimate the underlying ECG signal while suppressing power-line interference. Unlike the notch filter, which may attenuate useful signal components near 50/60 Hz, the Kalman Filter preserves ECG morphology through recursive state estimation. This preservation improves feature extraction and contributes to more reliable arrhythmia classification.

6.2. 50 Hz PLI Results

The output SNR is used to quantitatively distinguish between filtering outputs, while the denoised reconstructed signal is used to contrast them qualitatively. By adding 50 Hz PLI noise at 15 dB input SNR to an ECG recording of 100, a noisy signal was created.

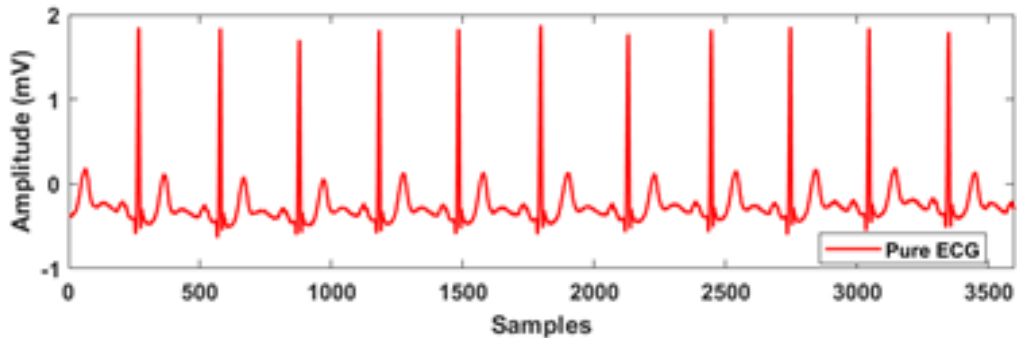


Figure 6.5: Clean ECG

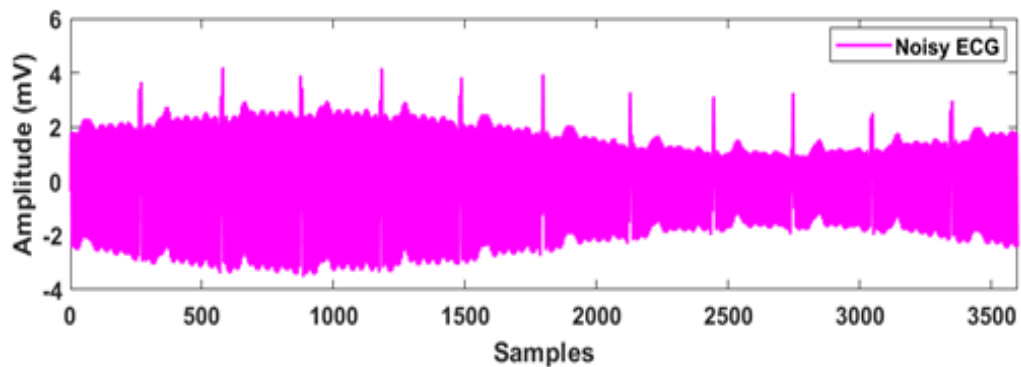


Figure 6.6: Noisy ECG

Proposed objective findings are shown in Figure 6.6 and Figure 6.7. The R-peak amplitude of some samples has been found to decrease at low SNR levels, although the notch filter is an efficient denoising tool. This happens even at low SNR when the notch filter successfully detects the existence of 50 Hz PLI noise.

Figure 6.6 displays filtering outcomes produced by the suggested approach. As demonstrated, the suggested technique effectively eliminates 50 Hz PLI noise from the ECG signal while maintaining a high degree of structural integrity. These denoising findings show that the suggested method works better than the notch filter at preserving the ECG's original diagnostic data. A quantitative examination of output SNR values for every technique was carried out to support this assertion.

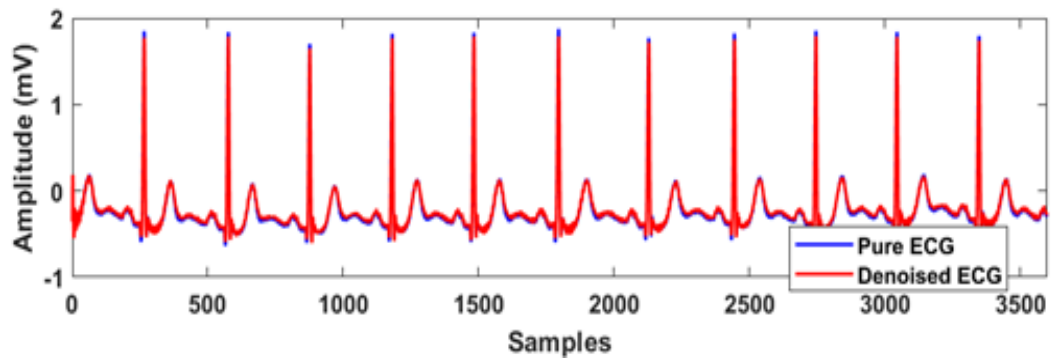


Figure 6.7: Notch Filter

Table 6.2: Denoising Results with 60 Hz with Notch Filter

Input SNR	Pid-100	Pid-110
-15 db	16.45	12.78
-20 db	17.85	12.57
-25 db	15.49	12.03
-30 db	13.09	10.75

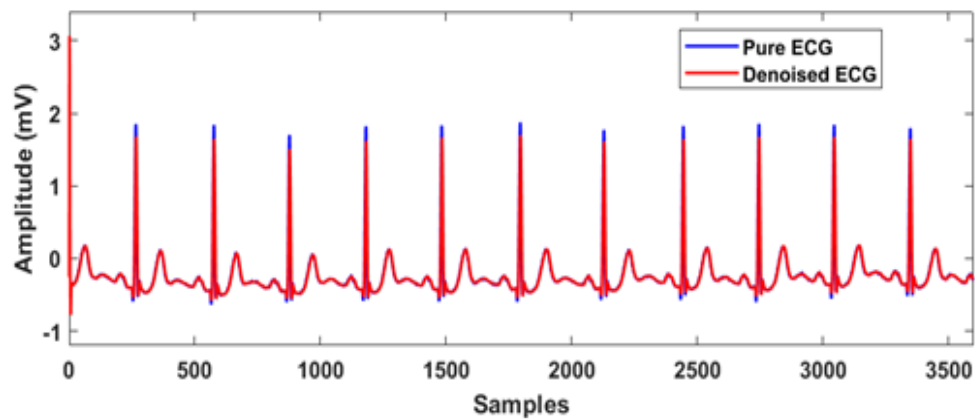


Figure 6.8: Proposed 50 Hz Removal Denoising Results for ECG 100 at 15dB.

As shown in Table 6.2, it demonstrates that other methods have a worse SNR for the output compared with the methodology being provided. While the SNR for the notch filter is 17.85 dB, the observed SNR with -20db for KF is 23.20 dB. Visual evaluation of several biological signals is frequently necessary for accurate diagnosis of many cardiac disorders, with ECG being a vital tool for identifying irregularities in heart rhythm. In this study, 50 and 60 Hz PLI are removed from ECG data using the suggested dynamical model and KF. Furthermore, the state estimation processes are used to efficiently reduce noise at these frequencies while maintaining important clinical information. The output SNR that results demonstrates how well KF performs in comparison to the notch filter.

Denoising PLI at negative SNR-contaminated electrocardiogram signals by applying KF is an enticing procedure to boost the quality of ECG signals and helps in adequate diagnosis and line of treatment of cardiac diseases. Hence, the proposed research objective provides the most accurate ECG signal analysis, which can be very useful for denoising ECG signals.

6.2.1. Real-Time TKF ECG Pre-Processing Results

In what seems to be a technological Age of Innocence, MIT Media Lab scientist David Rose presented a "vision of the future" in which technology atomises, merging with items that constitute everyday life. These developments will become ingrained in our surroundings, improving interpersonal interactions and fostering the desire for creativity, longevity, and omniscience. The fantastical creatures from science fiction and fairy tales will come to life [102].

Perhaps the most neglected source of enchantment in the fantasy game of chanting is the patients' imaginative interaction with such illogical mediations, along with a design philosophy that guides their imagination toward understanding these experiences [103].

Clinical ECG data and demographic information about patients and physicians in the Amravati District of Maharashtra, India, were gathered to do real-time patient ECG analysis, utilising the TKF. To assess cardiac rhythm states both before and after "OM" chanting sessions, 40 patients were chosen as a test group from a total sample size of 400. Each 90-minute session included instructions for patients to send their ECG results to medical specialists beforehand, and the health professional performed a follow-up ECG study right after the session.

Table 6.3 highlights the $\beta/(\theta + \alpha)$ ratio by comparing long-term practitioners (training subjects) with control (testing) participants. The table's right section shows data from the testing subjects, while the left half shows data from the training subjects, such as how long they had been practising mantra meditation. The γ/α ratio was found to rise during Focused Attention (FA) Meditation.

All 40 subjects had their γ/α ratio assessed; Table 6.3 shows the findings for 10 sample cases.

Table 6.3: Pre-and post-OM-chanting Patient Analysis for 90 minutes session

Patient ID	Age	Pre-OM-chanting (During 10 Min)		Post-OM-chanting (During 10 Min)	
		$\beta/(\theta + \alpha)$	(γ/α)	$\beta/(\theta + \alpha)$	(γ/α)
PID1	38	0.626	0.105	0.425	0.014
PID2	40	0.431	0.135	0.324	0.136
PID3	46	0.354	0.112	0.214	0.128
PID4	42	0.359	0.138	0.301	0.102
PID5	39	0.633	0.142	0.415	0.029
PID6	28	0.538	0.320	0.369	0.049
PID7	22	0.537	0.247	0.406	0.062
PID8	54	0.320	0.462	0.274	0.156
PID9	56	0.338	0.409	0.231	0.176
PID10	54	0.319	0.472	0.249	0.156

Based on these ratios, it can be concluded that OM chanting reduced the crucial peaks of cardiac arrhythmia since the patient had a dominating Beta and Gamma frequency relative to other frequencies, which are associated with the best possible heart rhythm. The outcomes of the TKF's application of ECG analogue-to-digital signal conversion are displayed in Figures 6.9 and 6.10.

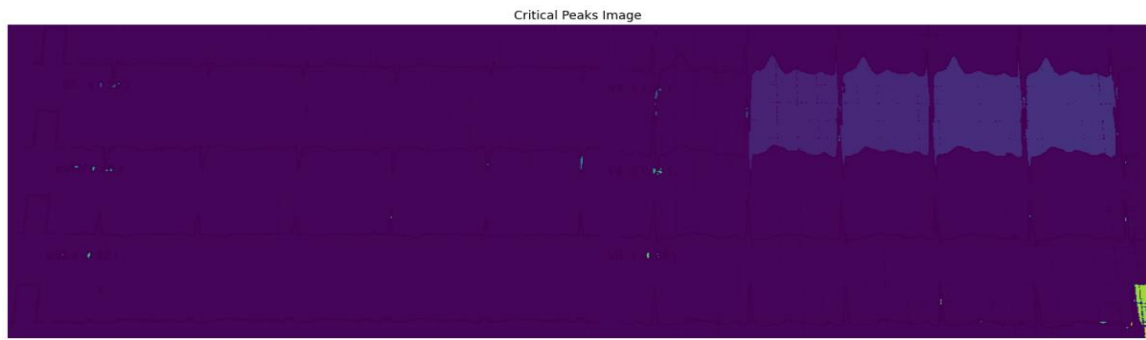


Figure 6.9: Pre-Enchanting Reading

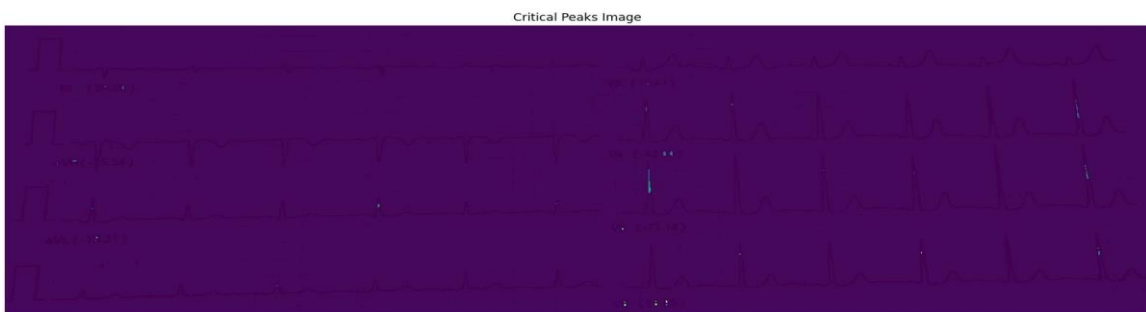


Figure 6.10: Post-Enchanting Reading

From Figure 6.10, it is observed that post-enchanting readings show the optimum frequencies as discussed in Table 6.3.

Further, the proposed research analysis revealed that the ECG digital analysis for the patient's test ($n=40$) is clearer than manual assessments of ECG physical reports. Consequently, we analysed the clarity of critical points and compared it to the physical ECG report analysis. The TKF signal preprocessing can handle PLI, and due to recurrent filtering, the ECG critical peaks can be recorded accurately.

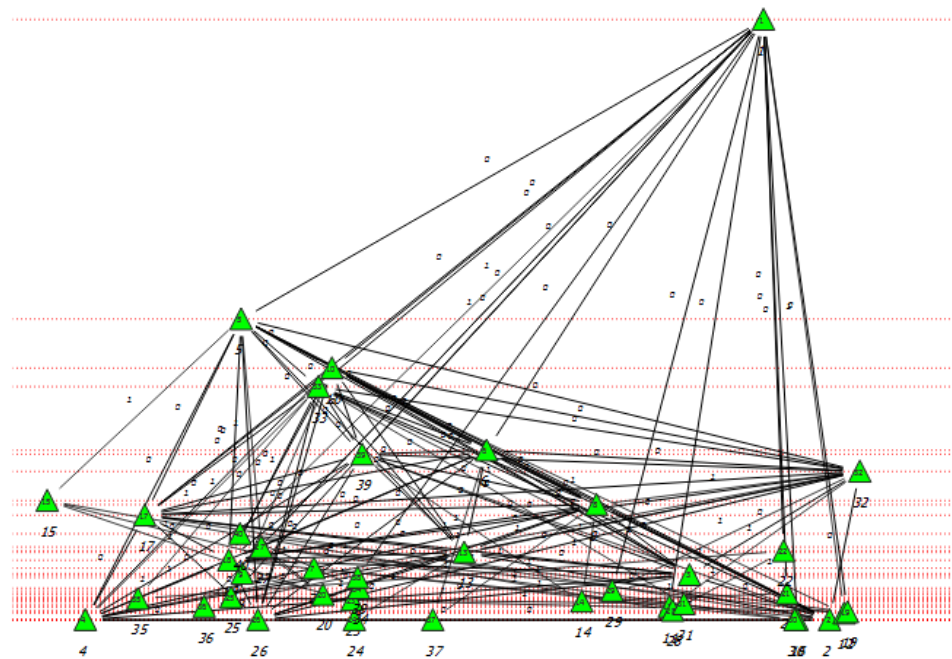


Figure 6.11: Overall Cardiac Arrhythmia Analysis Of 40 Patients for Accurate Visualisation of Critical Peaks

Figure 6.11 shows that the red node represents the highest discrepancy in reading, while green nodes are within the acceptable discrepancy, where exact identification of heart arrhythmias is performed as a post-Om-chanting session.

6.3. Performance Optimisation Results and Analysis

MIT-BIH-Arrhythmia dataset's R-R interval data is extracted and used in the ECG time series signal dataset. Completed testing and training for several types of cardiovascular illnesses. To reduce reconstruction errors, the 247,937 total trainable parameters were repeated using Self-attention-AE, validated on 15602 samples with an epoch size of 5 after being trained on 625004 samples of ECG time series signals. Figure 6.12 illustrates the LSTM sequential execution with Self-attention-AE.

Layer (type)	Output Shape	Param #
lstm_1 (LSTM)	(None, 1, 128)	66560
lstm_2 (LSTM)	(None, 64)	49408
repeat_vector_1 (RepeatVecto	(None, 1, 64)	0
lstm_3 (LSTM)	(None, 1, 64)	33024
lstm_4 (LSTM)	(None, 1, 128)	98816
time_distributed_1 (TimeDist	(None, 1, 1)	129
Total params: 247,937		
Trainable params: 247,937		
Non-trainable params: 0		

Figure 6.12: Self-Attention-AE

After epoch 30, training and validation model losses are compared, as shown in the following Figure 6.13. As the loss is near zero, the model's prediction outperforms the proposed system.

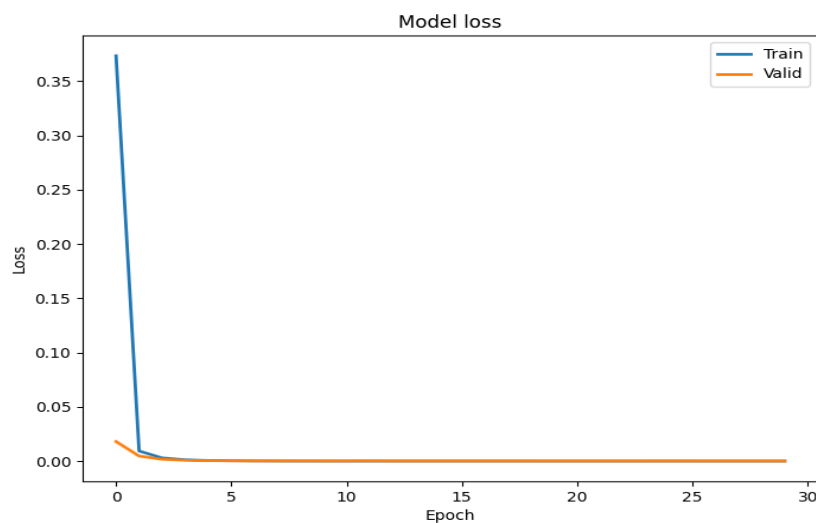


Figure 6.13. Training and Validation Model Loss For The Proposed System

Additionally, as seen in Figure 6.13, the classification error value recorded for various reconstruction error segment data points suggests that the classification error is extremely low, demonstrating the accuracy of the cardiovascular disease prediction result. To further reduce the classification errors and achieve the best

reconstruction error following Self-attention-AE execution, the suggested system will employ repeated training and validation.

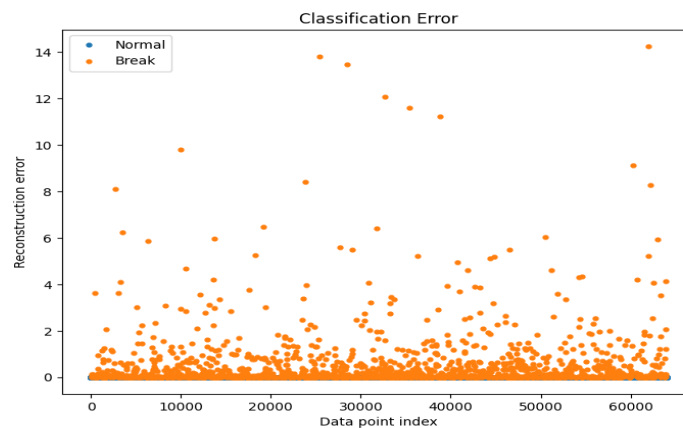


Figure 6.14: Classification Error for The Proposed System

Figure 6.14 shows that the model achieves an accuracy of 99.79% since mistakes across different classes are kept to a minimum. The high classification accuracy indicates that the Self-Attention Autoencoder effectively minimises reconstruction errors before classification. The learned feature representations improve class separability, enabling the classifier to distinguish subtle variations among arrhythmia types. The low number of false positives and false negatives in the confusion matrix further confirms the robustness of the proposed framework. The Self-Attention Autoencoder's recurrent assessment method, which successfully reduces reconstruction inconsistencies, is responsible for this outstanding performance. Although the proposed model achieved high overall accuracy, a small number of beats were misclassified. Most misclassifications occurred between PVC and VT beats because both classes exhibit similar QRS morphology and rhythm characteristics. Additionally, residual noise and inter-patient variability may have contributed to incorrect predictions. These observations indicate that incorporating additional morphological features or increasing the diversity of the

training data may further improve classification performance. Figure 6.14 illustrates the reconstruction error of the proposed Self-Attention Autoencoder for all ECG samples. Most data points exhibit reconstruction errors close to zero, indicating that the model accurately reconstructs the majority of ECG signals. However, a limited number of samples show comparatively higher reconstruction errors. These higher errors correspond to ECG beats that are either highly abnormal, contain significant noise, or possess waveform characteristics that differ substantially from the dominant training patterns. Consequently, the reconstruction error increases for these challenging samples.

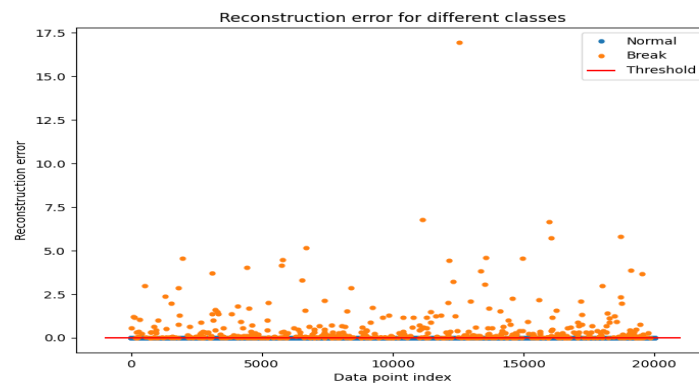


Figure 6.15: Reconstruction Error for the proposed system

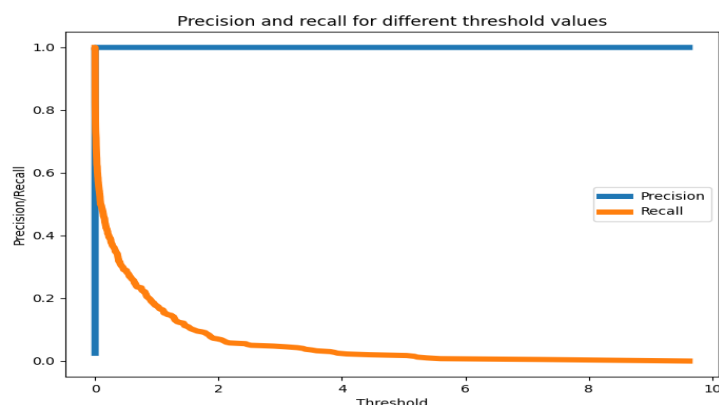


Figure 6.16: Recorded Precision and Recall Values

Figure 6.16 presents the variation of precision and recall with respect to different classification thresholds. At lower threshold values, the classifier detects almost all positive ECG beats, resulting in very high recall. As the threshold increases, the classifier becomes more conservative, reducing false-positive predictions while simultaneously decreasing recall. This behaviour demonstrates the inherent trade-off between precision and recall observed in supervised classification systems. The proposed model maintains high precision across the practical operating threshold, indicating reliable identification of arrhythmia classes with minimal false alarms.

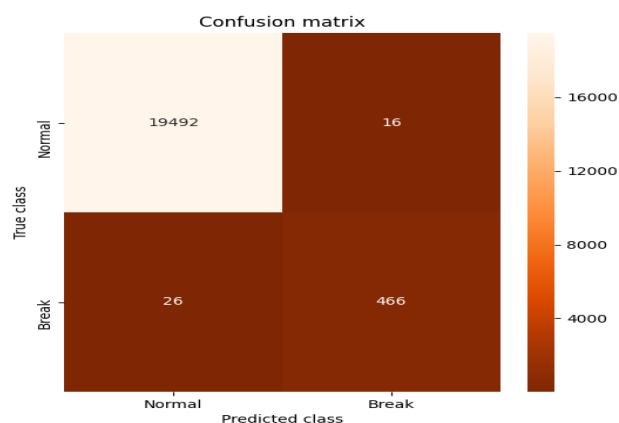


Figure 6.17: Confusion Matrix for The Proposed Self-Attention-AE Model

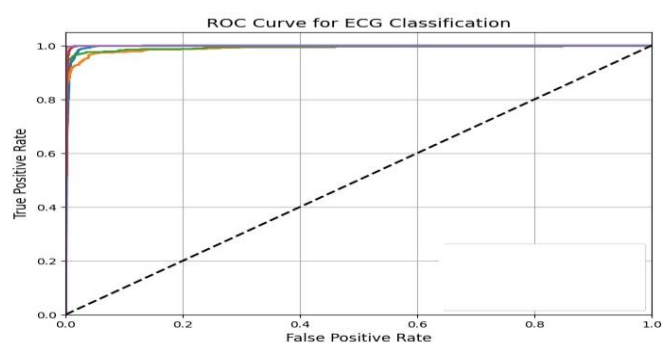


Figure 6.18: ROC Curve for the Proposed Model

The proposed model achieved an accuracy of 99.79%, indicating excellent overall classification performance. A precision of 96.68% demonstrates a low false-positive rate, while a recall of 94.72% indicates that most abnormal beats were correctly identified. The F1-score of 95.69% reflects a good balance between precision and recall, and the specificity of 99.92% confirms the model's strong ability to correctly identify normal beats.

Table 6.4 displays an evaluation of the confusion matrix for normal and break labels, which was obtained from training and validation of several classes. The confusion matrix indicates that only a small number of beats were misclassified. These misclassifications occurred between arrhythmia classes with similar ECG characteristics.

Table 6.4 Confusion Matrix for Proposed Self-Attention-AE.

Self-attention-AE	Positive	Negative
Positive	TP=19492	FP=16
Negative	FN=26	TN=466

The confusion matrix indicates that only a small number of beats were misclassified. These errors mainly occurred among arrhythmia classes with similar ECG characteristics. Such misclassifications are likely due to overlapping waveform morphology and minor residual noise. Despite these errors, the low misclassification rate demonstrates the robustness of the proposed framework.

The Next Section discusses comparative analysis in two ways: 1) Comparison between the proposed AI-Dense Fit model and the Self-attention-AE model, and 2) Comparison between existing systems and the proposed system.

6.4 Chapter Summary:

This chapter offers a comprehensive performance analysis of the proposed arrhythmia classification framework. It evaluates system efficiency for ECG signal denoising, classification accuracy, and real-time applications using both benchmark datasets (such as MIT-BIH) and clinical ECG data.

The chapter first investigates ECG denoising under power line interference (PLI) at 60 Hz and 50 Hz using the output Signal-to-Noise Ratio (SNR) as a metric. Visual and quantitative results demonstrate that the Kalman Filter (KF)-based method outperforms the traditional notch filter, particularly in preserving diagnostic features such as R-peaks. The output SNR with -20db for KF has values of 23.20 dB, surpassing the notch filter's values of 17.85 dB.

Real-time evaluation was performed using clinical ECG data from 40 patients in Amravati, Maharashtra, assessing pre- and post-"OM" chanting effects. TKF preprocessing showed significant improvements in heart rhythm through enhanced $\beta/(\theta+\alpha)$ and γ/α ratios, supporting the clinical relevance of the system.

Furthermore, performance optimisation using a Self-Attention Autoencoder (AE) was implemented on the MIT-BIH dataset. The model achieved a classification accuracy of 99.79 % with minimal classification error. Performance was validated via confusion matrix analysis and metrics like precision and recall, highlighting the model's robustness and high reliability in arrhythmia classification.

Overall, the proposed system demonstrates superior noise removal, maintains clinical signal integrity, and delivers highly accurate classification results, making it suitable for real-world, real-time cardiac diagnosis applications.

Misclassified beats generally occur because some arrhythmia classes have similar ECG morphologies, making them difficult to distinguish. Additional factors such as residual noise, inter-patient variability, class imbalance, and slight variations in heartbeat patterns can also contribute to classification errors. Although these factors led to a small number of misclassifications, the proposed model maintained high overall classification performance. The observed misclassifications are plausible because certain arrhythmia classes share similar waveform characteristics, particularly in the QRS complex and RR intervals. In addition, residual noise, inter-patient variability, and class imbalance may reduce class separability, leading to occasional incorrect predictions. Future work will focus on increasing the diversity of the training dataset, incorporating additional morphological and temporal ECG features, optimising the attention mechanism, and applying data augmentation techniques. These improvements are expected to enhance feature discrimination and reduce misclassification among clinically similar arrhythmia classes.

CHAPTER 7

COMPARATIVE ANALYSIS AND DISCUSSION

This chapter provides a comparative analysis of the proposed arrhythmia classification framework against existing methods. The discussion is structured around key performance indicators, including classification accuracy, noise robustness, computational efficiency, and real-time applicability.

7.1. Comparison With Traditional Models

The comparison with the execution of existing algorithms also compares the results of both proposed models. LR, KNN, SVM, DT, Random Forest, and XGBoost to identify methodological and performance differences.

As previously stated, the suggested method carefully assesses each of the distinct waves for a single pulse. The findings are noteworthy, as seen in Figure 7.1. Finding the "Q" wave element, a known dangerous heartbeat amid random heartbeats among the normal (N), supraventricular ectopic (S), fusion (F), ventricular ectopic (V), and unknown (Q) heartbeats, has the potential to save lives, especially in patients with co-morbidity. This vital diagnosis helps predict a patient's cardiac arrhythmia state and has the potential to save lives.

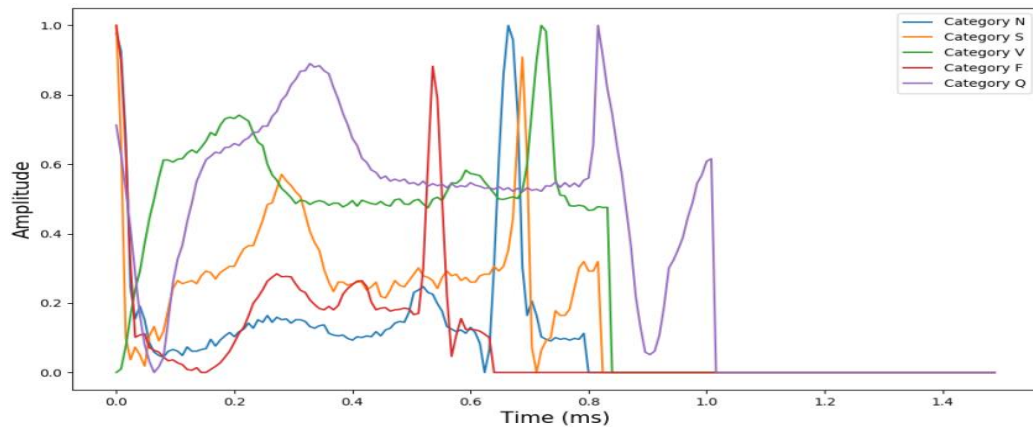


Figure 7.1: Classification of the ECG signal for a Single beat sinus

After detecting the ‘Q’ wave element using the proposed system, analysed the pre- and post- ‘OM’ enchanting impact on ‘S’, ‘V’, ‘F’, and ‘Q’ wave elements to understand the impact of ‘OM’ enchanting on the status of cardiac arrhythmia. We tested the proposed model on a real-time dataset of 400 patients (which is tested for the analysis of “OM” enchanting) and the MIT-BIH Arrhythmia dataset; training and testing were done for analysis of the proposed model. The model was trained on 109150 samples and validated on 4000 samples. By multiple testing scenarios of epoch sizes 20, 25, 50, and 75, we found that performance is excellent at the fixed epoch size of 75. Adam optimiser with the changing learning rate mechanism is applied to minimise the validation loss. The accuracy of the proposed model is 98.00%. Further ‘AI-DenseFit’ results are compared with other classifiers.

SNR	-5dB			0dB			5dB			-20 dB			20 dB		
Method	SN R _{imp}	RM SE	PR D%	SN R _{imp}	RM SE	PR D%	SNR imp	RM SE	PR D%	SN R _{im} p	RM SE	PR D%	SN R _{imp}	RM SE	PRD %
Proposed model with TKF	24.0 0	0.05 5	22. 1	20. 4	0.0 245	12	14.0 5	0.0 10	7.2 5	24. 50	0.0 60	22. 90	24. 99	0.0 80	23.05
Successive local filtering [71]	12	NR	NR	11. 7	NR	NR	10.6	NR	NR	NR	NR	NR	NR	NR	NR
ACDAE [72]	23.7 3	0.04 33	21. 1	19. 07	0.0 235	11	13.0 8	0.0 092	6.9 0	NR	NR	NR	NR	NR	NR

NR – Not Reported

Table 7.1: State-of-the-art Analysis Signal Denoising

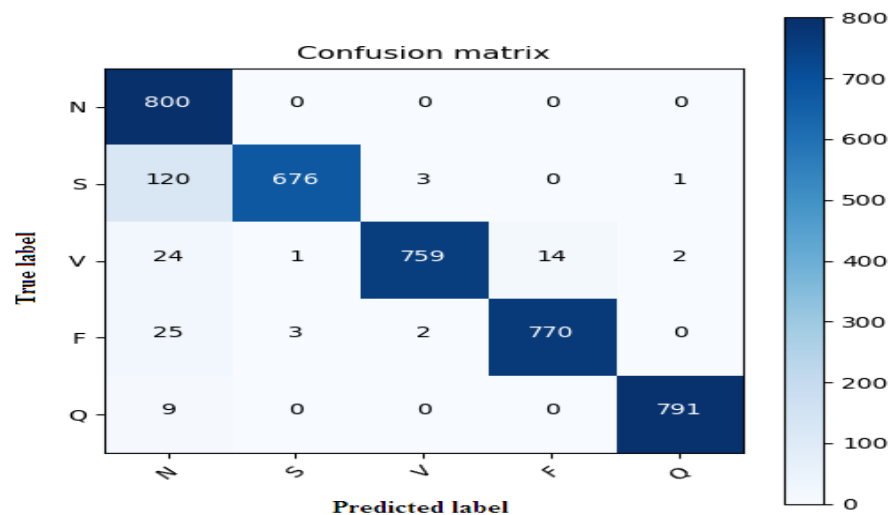


Figure 7.2: Confusion Matrix for proposed AI-Dense Fit Model

When analysing ECG time-series data, the suggested method achieved an exceptional accuracy of 98.00%, focusing on R-R peaks. Together with zero classification mistakes, this accomplishment sets a new standard for the prediction of cardiovascular illness. Table 7.1 further emphasises this by providing a detailed comparison between the proposed model, TKF, and existing models.

Further, the proposed Self-attention-AE model's result is compared with existing systems, as shown in Table 7.2.

Table 7.2 Experimental Results for Self-attention-AE.

Method	Dataset	Accuracy	Precision	Recall	F1-score	AUC	Year	Limitation
CNN-LSTM [74]	MIT-BIH	97.8	98.2	98.0	98.1	0.98	2023	Sensitive to noise
ACDAE [72]	MIT-BIH	98.88	98.76	98.48	98.62	0.99	2024	Higher complexity
Proposed Model Self Attention AE	MIT-BIH + Clinical	99.17	99.91	99.86	99.88	0.999	Proposed	Robust under noisy ECG

From Table 7.2, the comparative analysis, it is noted that the Self-attention-AE experimental results indicate improved performance compared with the selected baseline methods. As discussed in the proposed methodology, we trained and tested the proposed models (AI-Dense Fit and Self-attention-AE) with existing classifiers: LR, SVM, XGBoost, and DT. The superior performance of the proposed framework is primarily attributed to the integration of the Tuned Kalman Filter, which effectively suppresses ECG noise while preserving diagnostic wave morphology, and the Self-Attention Autoencoder architecture, which simultaneously captures both local morphological characteristics and long-term temporal dependencies. This combination improves feature representation and enhances generalization across different heartbeat categories. The comparative analysis results are depicted in Table 7.3.

Table 7.3: State-of-the-Art Performance Comparison

Machine learning method	Accuracy (%)
Proposed Self-attention-AE	99.17
Proposed AI-DenseFit	98.00
Logistic Regression	79.06
Support Vector Machine	72.90
XGBoost	83.85
Decision Tree	72.80

We recorded 0.965 average precision for real-time data and a loss of 0.019, where the base coverage error for the entire dataset is recorded as very little, with a value of 1.077. Compared to existing systems, the proposed AI-Dense Fit model outperforms existing systems with an accuracy of 98.00%. As a performance optimisation, the proposed Self-attention-AE model outperforms existing systems with an accuracy of 99.17%. Hence, the proposed model execution reveals that the classification results are extremely helpful for precisely predicting ECG components leading to cardiac arrhythmia diseases.

The selection of the proposed hybrid approach, comprising a Tuned Kalman filter, a Self-Attention Autoencoder, and an LSTM, is grounded in several key considerations aligned with the research objectives. First, the system demonstrates strong noise tolerance, particularly against power line interference (PLI), a common challenge in real-world ECG acquisition. The use of TKF dynamically suppresses such interference, improving signal clarity and ensuring reliable feature extraction. Second, by integrating signal filtering and classification into a unified

pipeline, the model is highly suitable for real-time applications, including wearable health monitors and edge-computing platforms. Third, the incorporation of the proposed model enables the network to adaptively focus on diagnostically significant portions of the ECG signal, improving generalisation across patients and signal variations. Additionally, the hybrid architecture exhibits notable performance gains. Preliminary experiments and comparative evaluations with existing models reveal that the TKF +Self-Attention Autoencoder-LSTM combination achieves higher classification accuracy and lower error metrics such as RMSE and PRD.

This methodology directly supports the overarching goal of developing a practical, intelligent system for early arrhythmia detection using real-world ECG data, especially within the context of emerging post-COVID cardiovascular risks. Furthermore, recent clinical data emphasise the importance of early rhythm regulation therapy in reducing the severity and mortality associated with AF, particularly among patients with existing CVD risk factors. These findings necessitate an enhanced focus on precise and timely arrhythmia classification. As a result, the proposed model is not only technically robust but also clinically relevant, supporting a paradigm shift in rhythm management strategies through early and accurate detection of AF episodes. This reinforces the importance of developing a novel algorithm that delivers improved classification performance while remaining suitable for deployment in real-world clinical and ambulatory settings.

This chapter details the methodological framework developed for a robust and real-time arrhythmia classification system, integrating advanced signal processing and deep learning techniques. A TKF was employed to perform adaptive denoising of

ECG signals, effectively mitigating power line interference and enhancing the clarity of diagnostic waveforms. The denoised signals were then passed through a Self-Attention Autoencoder-LSTM architecture, designed to capture spatial and temporal features of the heartbeat, enabling accurate classification from even short-duration or single-beat ECG segments.

To ensure diversity and practical relevance in the input data, the model was trained and validated using a diversified dataset that included real-world clinical ECG reports and records from the MIT-BIH Arrhythmia Database. Cross-validation, stratified sampling, and thorough preprocessing were used to increase robustness. Standard assessment criteria, such as accuracy, F1-score, and SNR, were used to evaluate the model's performance. The implementation closely followed ethical standards, such as informed consent and data protection, and made use of open-source resources including TensorFlow, WFDB, and several Python modules.

7.2 Limitations of the Proposed Framework

Despite the promising performance of the proposed Tuned Kalman Filter-based Self-Attention Autoencoder-LSTM framework, several limitations should be acknowledged. First, the proposed model was evaluated using the MIT-BIH Arrhythmia Database together with ECG recordings collected from 400 patients, which may not fully represent the diversity of ECG characteristics observed across different populations, healthcare institutions, and acquisition devices. Second, although the comparative study demonstrates improved performance over several conventional machine learning and recent deep learning methods, comparisons with additional state-of-the-art transformer-based architectures remain an area for future investigation. Third, computational aspects such as inference time, memory utilisation, and energy consumption were not

experimentally analysed because the primary objective of this work was to evaluate classification accuracy and denoising performance. Furthermore, formal statistical significance testing was not performed, and future studies should incorporate rigorous statistical validation to strengthen comparative conclusions. Finally, the proposed deep learning framework functions largely as a black-box model and integrating explainable artificial intelligence techniques could further improve its clinical transparency and acceptance.

7.3 Chapter Summary:

This chapter presents a thorough comparative evaluation of the proposed arrhythmia classification framework against traditional machine learning models and recent deep learning approaches. The analysis emphasises performance indicators such as classification accuracy, robustness to noise, computational efficiency, and real-time applicability. The proposed system integrates a Tuned Kalman filter for denoising and a hybrid Self-Attention Autoencoder architecture for classification, achieving superior results. Compared to classifiers like Logistic Regression, SVM, Decision Trees, and XGBoost, the proposed Self-Attention-AE and AI-DenseFit models achieved accuracy rates of 99.17% and 98.00%, respectively, significantly outperforming traditional methods. Experimental results from both benchmark (MIT-BIH) and real-time ECG datasets (400 patients) further validate the system's robustness and clinical applicability. Performance metrics, such as SNR improvement, RMSE, PRD, precision, and recall, confirm the proposed method's effectiveness in denoising and classification, even under varying noise levels (-20 dB). The framework also demonstrates strong generalisation capabilities across varied heartbeat types, including the detection of

clinically vital components like the Q-wave. The system supports real-time monitoring, shows high adaptability to post-COVID cardiovascular risks, and adheres to ethical standards. Ultimately, this chapter substantiates the model's suitability for clinical deployment in wearable and edge-computing environments, offering a scalable, intelligent solution for early arrhythmia detection and rhythm management.

CHAPTER 8

FEASIBILITY STUDY AND DEPLOYMENT ASSESSMENT

8.1 Introduction

The objective of this chapter is to evaluate the practical feasibility and acceptance of the proposed ECG classification system. Lifestyle-related parameters such as OM chanting and yoga-pranayama were included only to understand users' healthcare practices and attitudes toward preventive cardiac care. These variables were not incorporated into the proposed AI model and do not influence the classification algorithm or its performance.

Young people's sudden cardiac death (SCD) is a recent global concern, as covered in the previous chapters. Additionally, it has been observed that individuals with cardiac arrhythmias are more prone to different heart conditions. Classifying ECG data by hand can be prone to errors, and automation is undoubtedly required to effectively anticipate cardiac arrhythmia. The proposed self-attention artificial intelligence auto-encoder algorithm became an effective cardiac arrhythmia classification method through pre-processing by a novel TKF, which reduces the burden of pre-processing and improves the visibility of QRS complex and R-R peaks of the ECG waveform. The features were extracted using the Self-Attention artificial intelligence Autoencoder, which encoded the input ECG signals into a compressed latent space by capturing temporal dependencies and morphological patterns. The whole architecture of the Self-Attention-AE-based cardiac arrhythmia classification model is formed by passing these extracted features to a

Dense Neural Network classifier. With a precision of 99.91%, a recall of 99.86%, and an accuracy of 99.79%, the suggested method performs better than current models in categorisation and prediction of cardiac arrhythmias. It has been established that self-attention-AE-based training yields encouraging outcomes and helps diagnose complex cardiac diseases from ECGs to address actual cardiac issues.

Further, to identify the usability and convenience of the proposed system and to identify the acceptance for practical usage in the healthcare segment, we conducted a post-research feasibility analysis in Chapter 8 of the thesis. Hence, hypothesis formulation has been done in accordance with the need for the classification of cardiac arrhythmias. Section 8.2 gives the hypothesis formulation, which was later tested to identify the decision of the survey participants.

8.2 Statistical Hypothesis Testing Methodology:

The hypotheses were evaluated using Pearson's correlation coefficient because the study aimed to examine the linear relationship between the proposed ECG classification system and each evaluation criterion measured using five-point Likert-scale responses aggregated across 400 participants. Before hypothesis testing, questionnaire reliability was verified using Cronbach's Alpha, while sampling adequacy and construct validity were assessed using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity. All statistical analyses were performed at a significance level of $\alpha = 0.05$. The null hypothesis (H_0) was rejected whenever the p-value was less than 0.05, indicating a statistically significant relationship between the variables.

Table 8.1 Decision rule for Statistical Hypothesis

Step	Description
Step 1	Formulate H0 and H1
Step 2	Collect responses from 400 participants
Step 3	Verify reliability using Cronbach's Alpha
Step 4	Check sampling adequacy using KMO and Bartlett's Test
Step 5	Perform Pearson correlation analysis
Step 6	Use $\alpha = 0.05$ significance level
Step 7	If $p < 0.05$, reject H0 and accept H1

8.2.1 Hypothesis Formulation

The following hypotheses are for feasibility testing of the proposed research:

Hypothesis - I

H₀: The proposed system is not appropriate for the classification and prediction of heart arrhythmia

H₁: The proposed system is appropriate for the classification and prediction of heart arrhythmia

Hypothesis - II

H₀: There is no need for automated systems, and traditional ECG report analysis is sufficient to analyse heart arrhythmia classification

H₁: There is a need for automated systems, and traditional ECG report analysis is not sufficient to analyse heart arrhythmia classification.

Hypothesis - III

H₀: Proposed system SNR value is not better than traditional analogue ECG signal interpretation

H₁: The proposed system's SNR value is better than traditional analogue ECG signal interpretation

Hypothesis – IV

H₀: The proposed system is not better than the existing system

H₁: The proposed system performance is much better than the existing system

Hypothesis – V

H₀: The proposed system cannot be used as an add-on for medical facilities

H₁: The proposed system can be used as an add-on for medical facilities

Hypothesis – VI

H₀: Identification of a risky heartbeat cannot be useful for the prediction of sudden cardiac arrest

H₁: Identification of a risky heartbeat can be useful for the prediction of sudden cardiac arrest

8.3 Demographic Analysis

Table 8.2: Sample size

Respondent	Population	Sample
Patients and doctors residing in the Amravati District, Maharashtra, India	123600	400

We collected the demographic details of patients and doctors residing in the Amravati District, Maharashtra, India, for the proposed study. The questionnaire has been developed to evaluate the hypotheses. As per the reliability testing, 10% of the total sample size of 400 respondents, we conducted personal interviews with 30 patients, and the proposed system execution is demonstrated to 10 doctors. The questionnaires are attached to this analysis report.

Table 8.3: Gender Analysis

Gender	Frequency	Percentage
Male	153	38%
Female	247	62%
Total	400	100%

Table 8.4. Age Analysis

Age (years)	Frequency	Percentage
25-35	206	52%
36-46	194	48%
Total	400	100%

Table 8.5: Marital status

Marital status	Frequency	Percentage
Married	191	48%
Unmarried	209	52%
Total	400	100%

Table 8.6: Work Experience

Work Experience	Frequency	Percentage
1-3 years	63	16%
4-6 years	179	45%
More than 6 years	158	39%
Total	400	100%

Table 8.7: Education

Education	Frequency	Percentage
Diploma	174	44%
Graduate	201	50%
Postgraduate	25	6%
Total	400	100%

Table 8.8: Job Status

Job status	Frequency	Percentage
Working	259	65%
Not Working	52	13%
Left the job	89	22%
Total	400	100%

Table 8.9: OM chanting status

OM chanting status	Frequency	Percentage
Yes	241	60%
No	159	40%
Total	400	100%

Table 8.10: Yoga-pranayama practice

Yoga-pranayama practice	Frequency	Percentage
High	183	46%
Moderate	168	42%
Low	49	12%
Total	400	100%

8.3.1 Graphical Demographic Analysis

The table's data is represented graphically.

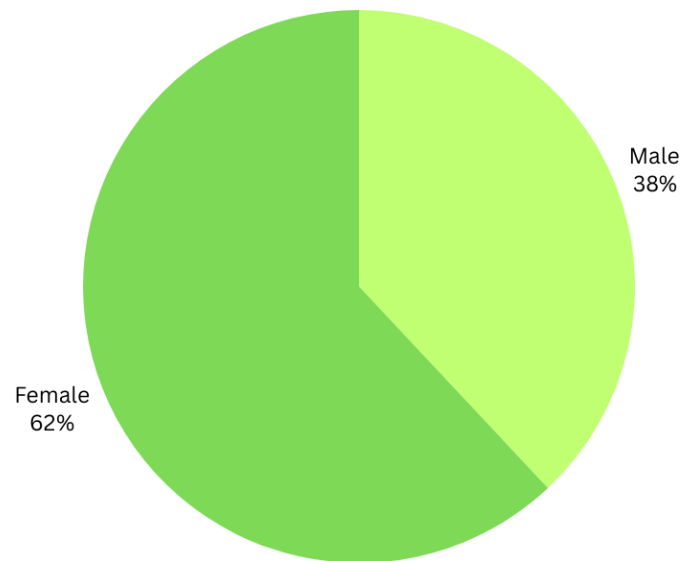


Figure 8.1: Gender

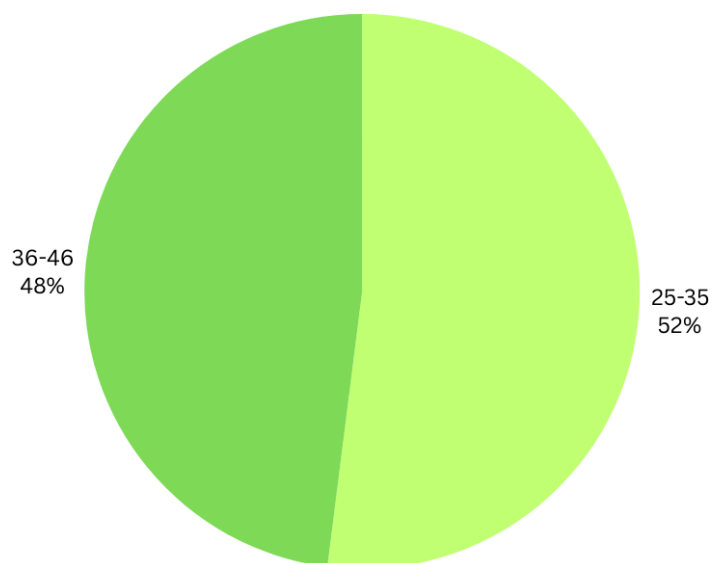


Figure 8.2: Age Analysis

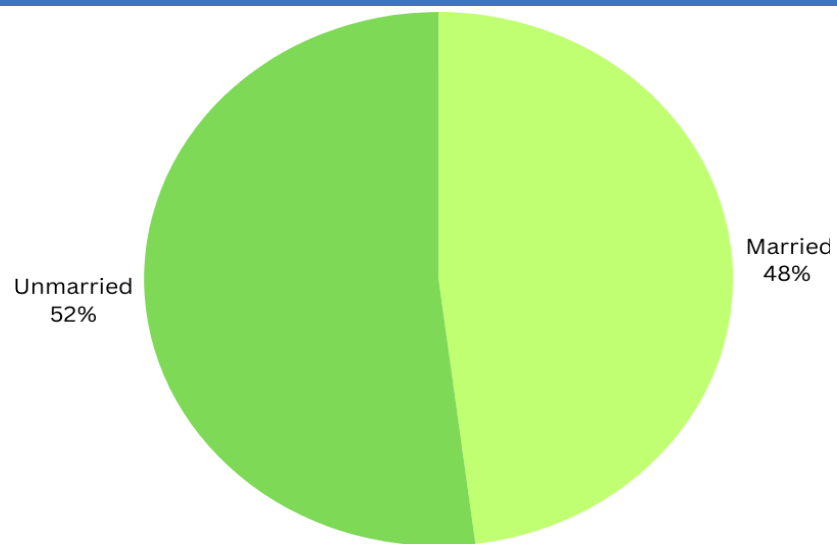


Figure 8.3: Marital status

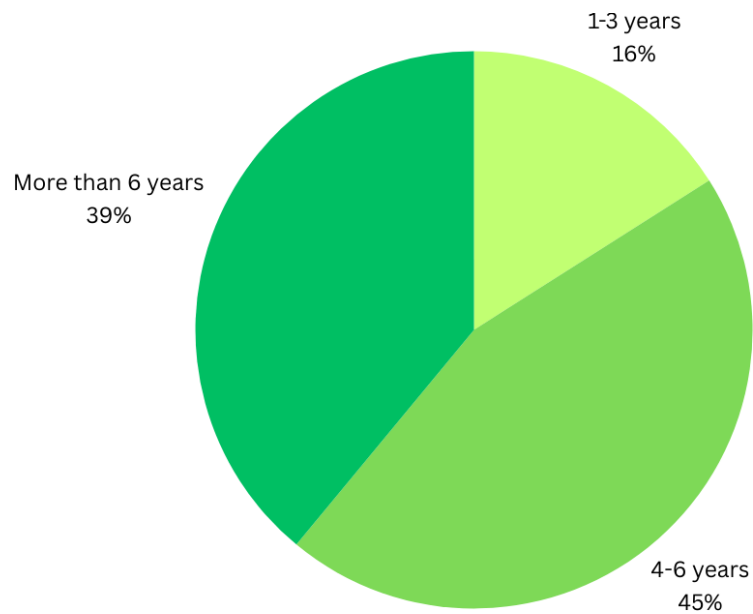


Figure 8.4: Work Experience

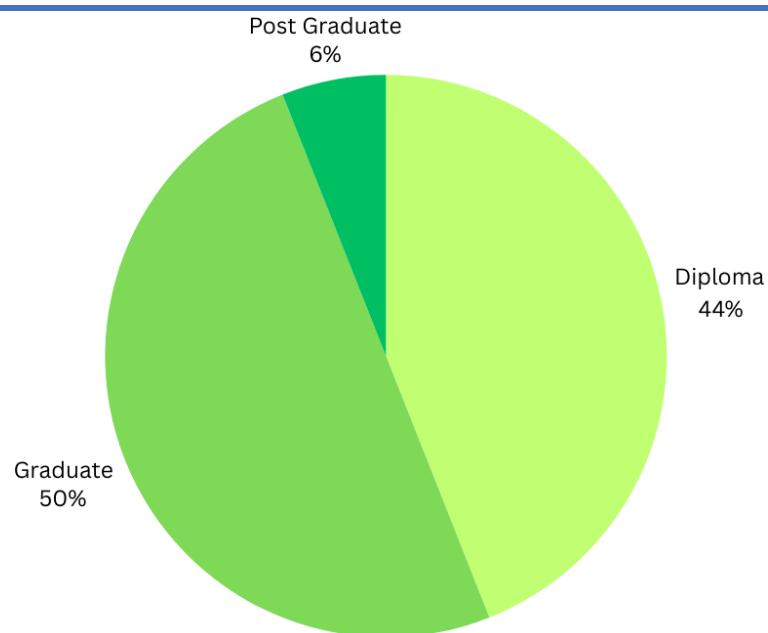


Figure 8.5: Education

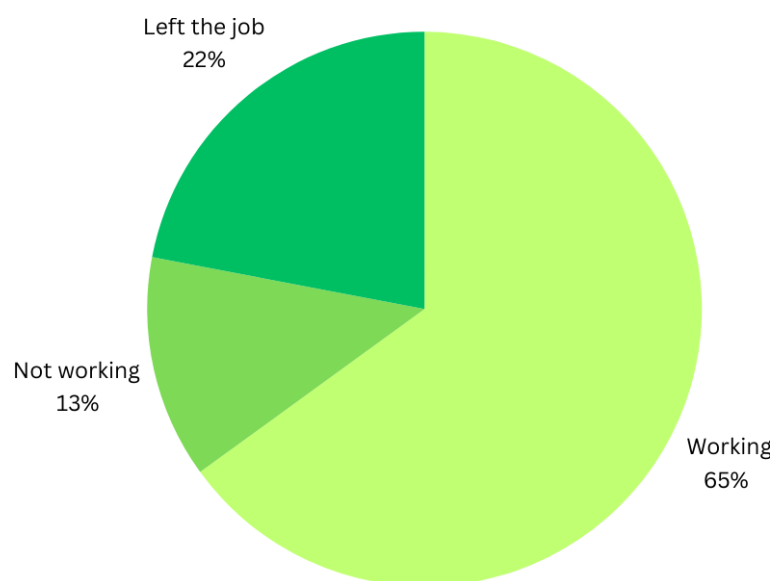


Figure 8.6: Job status

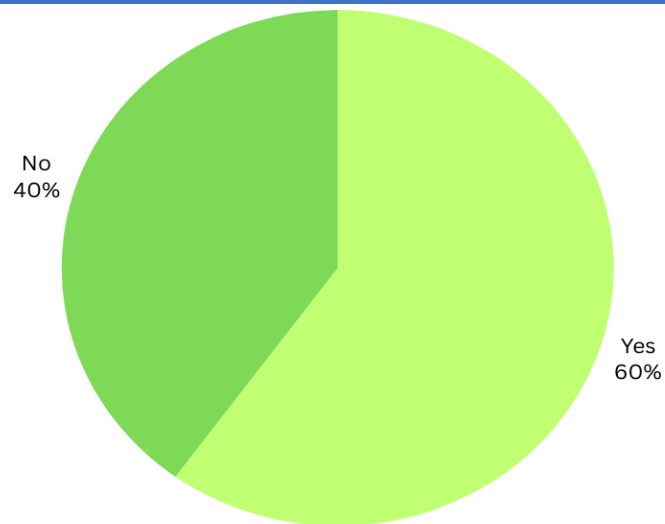


Figure 8.7: OM chanting status

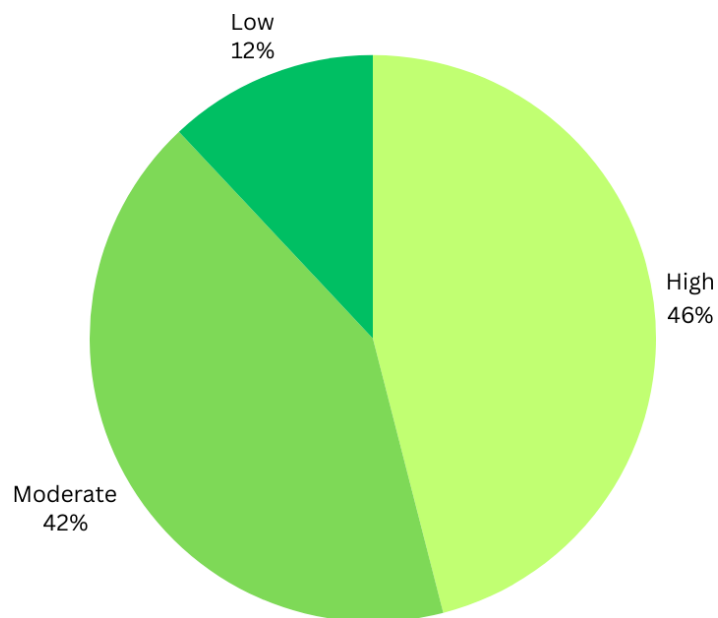


Figure 8.8: Yoga-Pranayama practice

Overall Interpretation:

38 per cent of respondents were male, and 62 per cent of respondents were female. Concerning age-wise classification, 52 per cent of respondents were in the age group between 25-35 years, and 48 per cent were in the age group between 36 – 46 years. Regarding marital status, 48 per cent of respondents are married, and 52 per

cent of respondents are unmarried. In terms of work experience, 16 per cent of respondents had one to three years of experience, 45 per cent had four to six years, and 39 per cent had more than six years.

Regarding educational qualification status, 44 per cent of respondents hold a diploma, 50 per cent of the respondents were graduates, followed by 6 per cent with post-graduation as their educational qualification. Tabulated data show that 13 per cent of respondents are not working, 22 per cent left their jobs due to illness, and 65 per cent are working.

Similarly, opinion about 'OM chanting status': 60% of employees are satisfactory about their OM chanting session benefits, whereas 40 percent of employees did not opt for OM chanting sessions but were willing to follow meditation to support cardiac arrhythmia cure. Further, looking at the yoga-pranayama practices, 12 per cent of respondents recorded low involvement in yoga-pranayama practices. 42 per cent of respondents can invest their time moderately in yoga-pranayama practices, whereas 46 percent of respondents revealed that they highly recommend yoga-pranayama practices to manage cardiac arrhythmia status.

In summary, the proposed research feasibility study, as Survey responses indicate that several participants perceived OM chanting and yoga-pranayama as complementary practices alongside conventional medical treatment. These observations represent participant opinions collected during the feasibility study and should not be interpreted as evidence of algorithmic performance or clinical efficacy.

8.4 Pearson Correlation Coefficient Analysis

The Pearson Correlation Coefficient Analysis is used when we want to quantify the strength and direction of a linear relationship between two continuous variables that are normally distributed. It helps determine if there's a significant positive, negative, or no correlation between these variables.

To identify the relationship of all variables with the classification and prediction of heart arrhythmia, we conducted a Pearson correlation analysis. Pearson's correlation coefficient is a statistical measure of the strength of a linear relationship between paired data. In a sample, it is denoted by 'r', and it is constrained as:

$-1 \leq r \leq 1$ and the formula is given as:

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \quad (\text{Eq 8.1})$$

A positive value of 'r' denotes positive linear correlation, a negative value denotes negative linear correlation, and zero denotes no linear correlation; the closer the value is to 1 or -1, the stronger the linear correlation. Regarding Evans' (1996) scale, the absolute value of 'r' is considered, as shown in Table 8.10. Pearson's correlation coefficient was selected because the objective was to measure the strength and direction of the linear association between the proposed system and the evaluation variables. The collected responses were converted into numerical scores using a five-point Likert scale and analysed as continuous variables for correlation analysis.

Table 8.11: Five Likert Scales

0.00-.19	Very weak
0.20-.39	Weak
0.40-.59	Moderate
0.60-.79	Strong
0.80-1.0	Very strong

According to the hypothesis formulation in Section 8.2 of this thesis, the hypothesis testing has been conducted as follows:

Hypothesis I:

H₀: H₀: The suggested approach is unsuitable for categorising and forecasting cardiac arrhythmias

H₁: The suggested system is suitable for categorising and forecasting cardiac arrhythmias.

Table 8.12: Classification and prediction of heart arrhythmia

		Proposed system	Classification and prediction of heart arrhythmia
Proposed system	1-tailed Pearson Correlation Sig. N	1 400	0.809 0.001 400
Classification and prediction of heart arrhythmia	1-tailed Pearson Correlation Sig. N	0.809 0.001 400	1 400

At the 0.05 level, the correlation between the suggested system and itself is $r = 1$, and there are 400 non-missing observations for height. The suggested system demonstrates a correlation of $r = 0.809$ with the classification and prediction of cardiac arrhythmias based on 400 observations with pairwise non-missing values. Furthermore, using $n = 400$ non-missing observations for weight, classification, and the prediction process's correlation with itself is $r = 1$. There is a statistically

significant linear association between the proposed approach and the classification and prediction of cardiac arrhythmias ($r=0.809$, $p<0.05$). There is a positive correlation between the suggested system and the classification and prediction of cardiac arrhythmias. The affirmative hypothesis is therefore accepted.

Hypothesis II:

H₀: There is no need for automated systems, and traditional ECG report analysis is sufficient to analyse heart arrhythmia classification

H₁: There is a need for automated systems, and traditional ECG report analysis is not sufficient to analyse heart arrhythmia classification.

Table.8.13: Traditional ECG Analysis

		Automated systems	Traditional ECG analysis
Automated systems	Pearson Correlation Sig. (1-tailed) N	1 400	0.811 0.003 400
Traditional ECG analysis	Pearson Correlation Sig. (1-tailed) N	0.811 0.003 400	1 400

The number of non-missing observations for height ($n=400$) and the correlation of automated systems with themselves ($r=1$) are both significant at the 0.05 level (1-tailed). Based on 400 observations with paired non-missing data, there is a correlation ($r=0.811$) between automated methods and traditional ECG analysis. Correlation between the number of non-missing observations for weight ($n=400$) and traditional ECG analysis with itself ($r=1$). There is a statistically significant linear association between automated systems and traditional ECG analysis ($r=0.811$, $p<0.05$). The association is positive, meaning that there is a positive

correlation between automated systems and conventional ECG analysis. The affirmative hypothesis is therefore accepted.

Hypothesis - III

H₀: Proposed system SNR value is not better than traditional analogue ECG signal interpretation

H₁: The proposed system's SNR value is better than traditional analogue ECG signal interpretation.

Table 8.14: Analogue ECG Signal Interpretation

		Proposed system SNR	Analogue ECG signal interpretation
Proposed system SNR	Pearson Correlation Sig. (1-tailed) N	1 400	0.756 0.001 400
Analogue ECG signal interpretation	Pearson Correlation Sig. (1-tailed) N	0.756 0.001 400	1 400

The number of non-missing data for height ($n=400$) and the correlation of the proposed system SNR with itself ($r=1$) are both significant at the 0.05 level (1-tailed). Analogue ECG signal interpretation and the proposed system's SNR correlate ($r=0.756$) based on 400 observations with pairwise non-missing values. Correlation between the number of non-missing observations for weight ($n=400$) and interpretation of the analogue ECG signal with itself ($r=1$). A statistically significant linear association ($r=0.756$, $p<0.05$) exists between suggested system SNR and interpretation of analogue ECG data. The association is positive in

direction, meaning there is a positive correlation between suggested system SNR and interpretation of the analogue ECG data. The affirmative hypothesis is therefore accepted.

Hypothesis – IV

H₀: The Proposed system is not better than the existing system

H₁: The proposed system is better than the existing system

Table. 8.15: Comparison of the proposed system and the existing system

		Proposed system	Existing system
Proposed system	Pearson Correlation	1	0.862
	Sig. (1-tailed)		0.002
	N	400	400
Existing system	Pearson Correlation	0.862	1
	Sig. (1-tailed)	0.002	
	N	400	400

The number of non-missing observations for height ($n=400$) and the correlation of the proposed system with itself ($r=1$) are significant at the 0.05 level (1-tailed). Based on 400 observations with pairwise non-missing values, the proposed system and the existing system correlate ($r=0.862$). correlation between the current system and itself ($r=1$) and the quantity of weight-related non-missing observations ($n=400$). There is a statistically significant linear relationship between the proposed system and the existing system ($r=0.862$, $p<0.05$). The association is positive in direction, meaning there is a positive correlation between the suggested system and the current system. The affirmative hypothesis is therefore accepted.

Hypothesis – V

H₀: The proposed system cannot be used as an add-on for medical facilities

H₁: The proposed system can be used as an add-on for medical facilities.

Table. 8.16: Proposed System Add-on Medical Facilities

		Proposed system	Add-on for medical facilities
Proposed system	Pearson Correlation	1	0.891
	Sig. (1-tailed)		0.003
	N	400	400
Add-on for medical facilities	Pearson Correlation	0.891	1
	Sig. (1-tailed)	0.003	
	N	400	400

Both the correlation of the suggested system with itself ($r=1$) and the number of non-missing observations for height ($n=400$) are significant at the 0.05 level (1-tailed). $R=0.891$ is the correlation between the suggested system and add-on for medical facilities based on $n=400$ observations with pairwise non-missing values. In addition to the number of weight-related non-missing observations ($n=400$) and the correlation between medical facilities and themselves ($r=1$). There is a statistically significant linear association between the suggested system and medical facility add-on ($r=0.891$, $p<0.05$). The association is positive in direction, meaning there is a positive correlation between the proposed system and the medical facility add-on. The affirmative hypothesis is therefore accepted.

Hypothesis – VI

H₀: Identification of risky heartbeat cannot be useful for the prediction of sudden cardiac arrest

H₁: Identification of high-risk heartbeats can be useful for predicting sudden cardiac arrest.

Table. 8.17: Prediction of Sudden Cardiac Arrest

		Risky heartbeat	Prediction of sudden cardiac arrest
Risky heartbeat	Pearson Correlation Sig. (1-tailed) N	1 400	0.905 0.001 400
Prediction of sudden cardiac arrest	Pearson Correlation Sig. (1-tailed) N	0.905 0.001 400	1 400

The number of non-missing observations for height ($n=400$) and the correlation of risky heartbeat with itself ($r=1$) are both significant at the 0.05 level (1-tailed). The prediction of sudden cardiac arrest and correlation of risky heartbeats ($r=0.905$) were derived from 400 data points with pairwise non-missing values. Correlation between the number of weight-related non-missing observations ($n=400$) and the prediction of sudden cardiac arrest with itself ($r=1$). There is a statistically significant linear link between the prediction of sudden cardiac arrest and risky heartbeat ($r=0.905$, $p<0.05$). The association is positive, meaning that there is a positive correlation between the prediction of sudden cardiac arrest and a risky heartbeat. The affirmative hypothesis is therefore accepted.

8.5 Descriptive Analysis

Based on the questionnaire survey responses, a descriptive analysis for all variables.

Table 8.18: Descriptive Statistics of Proposed System

Particulars	Mean	Std. Deviation
The proposed system is useful for the classification and prediction of heart arrhythmia	3.98	0.893
Automated systems are required for the classification and prediction of heart arrhythmia	3.79	0.876
Proposed system SNR values are better than those of existing systems with a Tuned Kalman filter	3.83	0.890
The proposed system can be used as an add-on facility with IoT, Cloud health monitoring, etc.	3.58	0.863
Identification of a risky heartbeat is useful for predicting sudden cardiac arrest	3.90	0.871
The proposed system is more feasible than the existing system	3.91	0.882

Interpretation:

Regarding the Proposed System, the item with the highest mean was "Proposed system useful for classification and prediction of heart arrhythmia" ($M = 3.98$, $S. D = 0.893$), which was followed by "Proposed system is more feasible as compared to existing system" ($M = 3.91$, $S. D = 0.882$). Identification of risky heartbeat is useful for prediction the sudden cardiac arrest' ($M = 3.90$, $S. D = 0.871$), Proposed system SNR values are better than existing systems with Tuned Kalman filter ($M = 3.83$, $S. D = 0.890$), Automated systems required for classification and prediction

of heart arrhythmia ($M = 3.79$, $S. D = 0.876$), and 'Proposed system can be used as add-on facility with IoT, Cloud health monitoring, etc.' with ($M = 3.58$, $S. D = 0.863$).

8.6 Data Reliability and Validity

A 5-point Likert scale (Gail M. Sullivan, 2013) to measure survey participants' opinions from options provided in the questionnaire, as: Extremely dissatisfied, Dissatisfied, Neutral, Satisfied, and Extremely satisfied. Cronbach's alpha reliability test was also employed to investigate internal consistency. The Cronbach's Alpha Reliability Test uses repeated trials to illustrate how results can be repeated. In technical terms, it refers to how well data from a questionnaire yields consistent outcomes when applied to several respondents.

What is the consistency or stability of scores among respondents? It should be highlighted that reliability pertains to scores rather than individuals. To put it another way, a questionnaire's dependability is determined by how well it replicates the engagement strategies under consideration. Reliability is indicated by how closely they agree on each respondent's score. Likewise, the degree to which a person's survey response stays consistent over time is another indication of reliability.

A questionnaire's reliability can be determined in some ways. These include the internal consistency method, split-half method, similar forms, and test-retest approach. The internal consistency method is the most often used technique for assessing reliability due to its simplicity of use. It performs well in field research. The homogeneity of the variables on a scale is the focus of internal consistency.

The degree of strong intercorrelation between the parameters determines how internally consistent a scale is. The most widely used generic reliability approximation technique is this one. Internal uniformity, or the degree of intercorrelation among the parameters that make up a scale, is the key to reliability in the internal consistency technique. It shows how similar the scale's parameters are to one another. Cronbach's alpha reliability coefficient is used to quantify internal consistency. Verifying and confirming the accuracy of the gathered data is essential before beginning any study. Cronbach's Alpha test is used to assess the data's dependability.

Formulas utilised are listed here:

$$\alpha = \frac{N}{N-1} \left(1 - \frac{\sum_{i=1}^N \sigma_{Y_i}^2}{\sigma_X^2} \right)$$

Where, α is Cronbach's Alpha, and 'N' total number of study parameters.

Here, N= 6.

The test was conducted using all six parameters tested during the descriptive analysis.

$$\alpha = \left(\frac{6}{6-1} \right) * \left(1 - \left(\frac{4.40574}{18.2105} \right) \right) = 0.9096791$$

After confirming the data's dependability with a calculated Cronbach's alpha of 0.9096791, we chose to proceed with additional statistical analysis.

Table 8.19: Descriptive Statistics and Cronbach's alpha for proposed study

	Mean	S. D	N	Cronbach's alpha reliability
Risky heartbeat identification	3.89	0.937	6	0.922
Better SNR value	3.87	0.911	6	0.908
Automated cardiac arrhythmia classification	3.91	0.905	6	0.907
Add-on utility for the ECG system	3.59	1.023	6	0.915
Higher prediction accuracy	3.92	1.085	6	0.899
Outperforming Tuned Kalman filter	3.89	1.056	6	0.906

8.6.1 Kaiser-Meyer-Olkin (KMO) and Bartlett's Test

Bartlett's Test and Kaiser-Meyer-Olkin (KMO) are used to gauge how strongly variables are related to one another. For a factor analysis to be considered adequate, the sample adequacy, as measured by the KMO, must be more than 0.5.

Table 8.19: Kaiser-Meyer-Olkin (KMO) and Bartlett's Test

Kaiser-Meyer-Olkin (KMO) and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.922
Bartlett's Test of Sphericity	Approx. Chi-Square	16056.002
	df	204
	Sig.	0.002

We used the Power BI tool with R to represent the participants' responses graphically. Figure 8.9 shows all 400 participants' coordination during the survey.

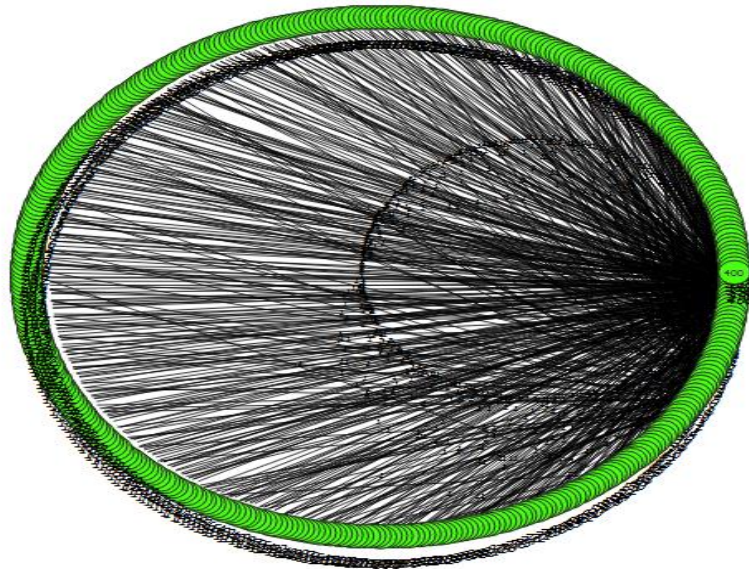


Figure 8.9: 400 participants' coordination during the survey

According to hypothesis testing, all survey respondents gave affirmative answers, as seen in the following figure, confirming that the suggested system is superior for classifying and predicting cardiac arrhythmias.

Further, Figure 8.10 shows the deviation in responses to questionnaires and shows there is very little deviation. Node numbers 1, 2, 3, and 5 are doctors who participated in the proposed study survey.

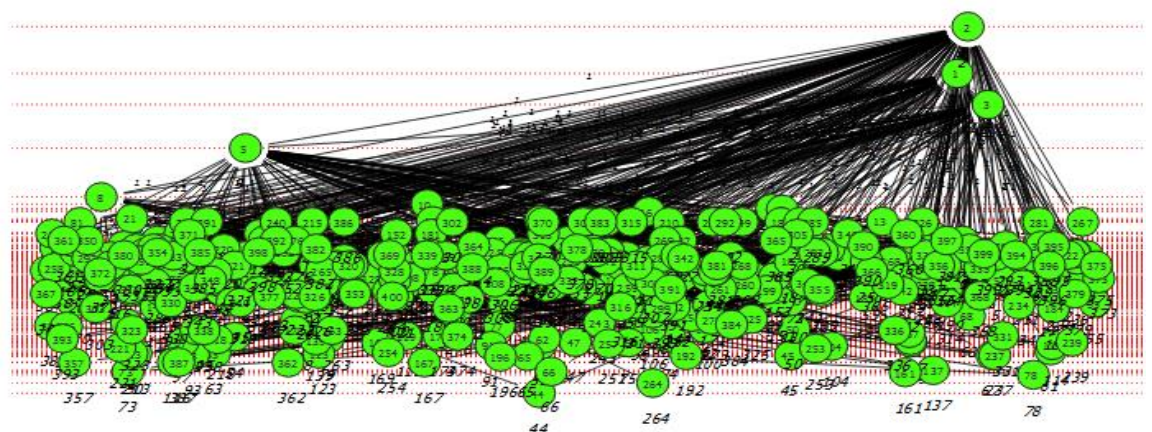


Figure 8.10: 400 participants' deviation in responses

As per a 10% reliability test for a total sample size (N=400), the following Figure 5.11 shows the Proposed system acceptance test results as per the statistical analysis of participants' responses. This demonstrates that both patients and medical experts believe the suggested system helps categorise and forecast cardiac arrhythmias.

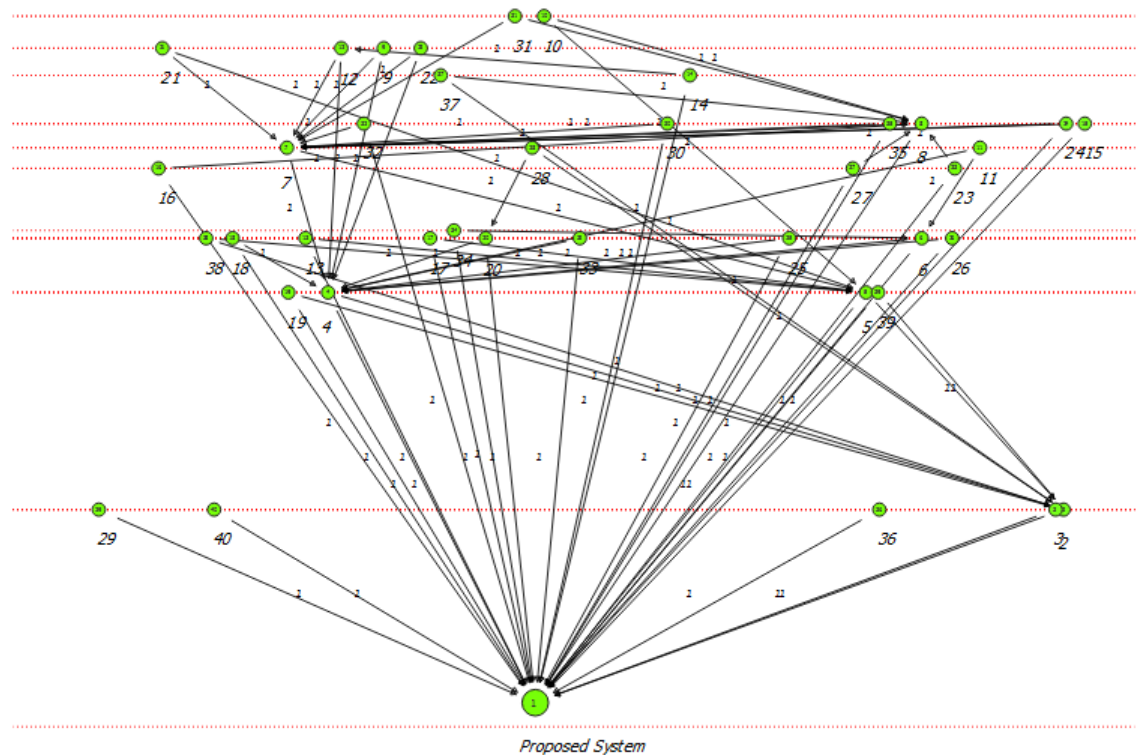


Figure 8.11: Proposed system acceptance test (N=40)

For any healthcare supportive system, it is important to know whether the system is convenient to use practically.

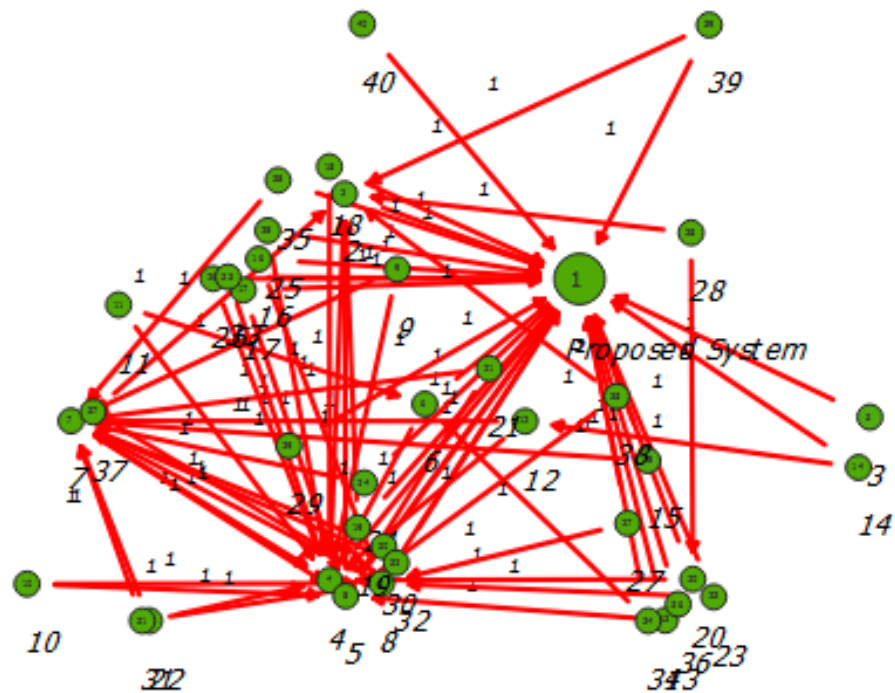


Figure 8.12: Proposed system convenience test (N=40)

Hence, to identify the practical usage convenience, we arranged a modest demo where doctors and patients can understand the QRS complex and R-R intervals, where risky heartbeats can be highlighted using a digital representation of the ECG report. Figure 8.12 shows that the respondents found that the proposed system is convenient without prior knowledge about the ECG components.

8.7 Chapter Summary:

This concluding chapter encapsulates the research contributions made toward developing an intelligent and real-time system for ECG-based arrhythmia classification. It summarises how the integration of a Tuned Kalman filter with a Self-Attention Autoencoder architecture enabled superior ECG signal denoising, efficient feature extraction, and highly accurate classification, even from short-

duration or single-beat signals. The model achieved a peak classification accuracy of 99.17%, with robust performance validated on both benchmark (MIT-BIH) and real-time clinical datasets. It demonstrated notable resilience to noise and generalizability across different heartbeat types, including life-critical components like the Q-wave. The study also validated the impact of “OM” chanting on ECG rhythms, expanding the system’s applicability in behavioural and clinical interventions. Ethical data handling, rigorous evaluation, and adherence to real-time constraints strengthen the model’s clinical relevance and deployment readiness.

Looking ahead, the chapter outlines several promising directions for future work. These include real-time deployment in wearable or edge devices, integration with IoT-enabled monitoring systems, and expansion to multiclass arrhythmia detection involving larger and more diverse datasets. Additional focus areas include the improvement of R-peak detection mechanisms, hardware optimisation for energy efficiency, and exploration of advanced hybrid deep learning models like Transformer variants. The research opens pathways for creating next-generation diagnostic tools that support early intervention and improved cardiac care, especially for patients at elevated post-COVID cardiovascular risk.

CHAPTER 9

CONCLUSIONS, RECOMMENDATIONS, and FUTURE SCOPE

9.1. Conclusions and Recommendations

According to the famous quote by Dr Robert C. Peale, "The best and most efficient pharmacy is within your system." The body system needs monitoring before any medicine. Historically, ancient Indian methodologies of meditation have always been keen to optimise the inner body pharmacy by controlling the most important organ, the Heart.

The heart is a single muscle that controls the whole body without interruption. Hence, the proposed research contributes to good heart health through the development of the proposed system. It is always better to prevent adverse effects than to undergo surgical attempts. Hence, prior knowledge of cardiac conditions is important for classification.

Looking back at the century-old history towards heart care, the first practical ECG or EKG was invented by Willem Einthoven in 1903. He developed a string galvanometer to measure the electrical activity of the heart, and his work earned him the Nobel Prize in Physiology or Medicine in 1924. Einthoven also established the concept of Einthoven's triangle, a system for placing electrodes on a patient's body to record the electrical signals from the heart. ECGs were initially used in hospitals and gradually became more widely adopted, eventually finding their way into portable devices like smartwatches. Since introducing the first ECG machine

to India in 1967, BPL has provided innovative cardiology solutions over the years, resulting in more effective healthcare delivery.

As need is the mother of invention, in the fast-paced world, new scenarios of cardiac care are being invented with the aid of artificial intelligence. Although a lot of research has been done on ECG analysis, nothing is known about combining a self-attention mechanism and DL model construction with ECG signal pre-processing. This novel method is essential for accurate abnormality analysis of ECG signals. As a result, the suggested study made three major advances to AE research by introducing a novel self-attention-based method:

- The proposed study implemented a Tuned Kalman filter to denoise ECG waveform (P, Q, R, S, T) components as discussed in this thesis.
- The implementation of the DL model using a novel self-attention-AE method is covered in the proposed study.
- To anticipate cardiac arrhythmias, the proposed study categorises ECG data.
- Additionally, the performance of the suggested self-attention-AE algorithm methodology and the innovative Tuned Kalman filter is compared with that of other methods.
- Finally, the post-research feasibility analysis is conducted to test opinions of respondents through the execution of a survey. The hypothetical analysis shows that the proposed research is useful for both doctors and patients to analyse cardiac arrhythmia.

- Additionally, OM enchanting and Yoga-pranayama session attendees are analysed statistically and verified that these techniques can lower cardiac arrhythmia symptoms.

Pre-processing will be carried out using the suggested self-attention-AE method by denoising ECG data with a novel Tuned Kalman filter, which can improve the clarity of the R-R peak cycle and QRS complex. Additionally, cardiac arrhythmia is identified through the classification of ECG signals. It is useful for early medical therapy to prevent potential health hazards because the categorisation result predicts different arrhythmic disorders. Most significantly, QRS complex and R-R peak analysis of ECG waveforms allow medical professionals to comprehend the condition of a single heartbeat, which otherwise behaves erratically due to a variety of patient diseases. The medical community should be encouraged by the possibility of early cardiac problem diagnosis and comprehension.

In a post-COVID-19 global scenario, much more of the population is suffering from cardiac arrhythmia for numerous reasons. The heart is a key organ that may contribute to life-threatening conditions. Hence, to provide a low-cost facility to monitor cardiac rhythm and include it as a routine checkup practice, just like many people are already aware of diabetes routine checkups as preventive care, the proposed system proved to be a successful model.

We revealed the answers to the Research Questions (RQ) to provide optimum conclusions for the study as follows:

RQ1: Which techniques are performing well compared to older research?

Under the existing system, results show that the Logistic Regression gives a classification accuracy for cardiac arrhythmia of about 79.06%, the Support Vector Machine accuracy reaches to 72.90%, XGBoost accuracy is mentioned as 83.85%, and the Decision Tree has an accuracy of 72.80%. Out of the selected existing methods for state-of-the-art comparison, Logistic Regression is noted as a well-performing technique compared to other techniques, with an accuracy of 79.06%. Hence, the proposed system is targeted at better accuracy of classification.

RQ2: What problems are handled by existing research?

The existing techniques handled problems like pre-processing of the dataset by labelling the missing values, eliminating the ambiguous values, and hyperparameter tuning. Also, in the case of real-time training and testing of the dataset, the results seemed to be defective due to a smaller number of patients' records. Further, accuracy defects are observed due to the insufficient PLI interference handling capacity, which results in the degraded accuracy of the classification.

RQ3: What are the challenges during the real-time patient study?

The core challenge during the real-time patient data collection is to segregate patients suffering from cardiac arrhythmia and to preprocess physically collected ECG reports, which need to be converted into digital form. The digital values of ECG reports are shared by the hospital, which is further used as a real-time dataset. Apart from these technical challenges, patient identity masking is necessary, as the image form of cropped ECG reports leads to pixel-level quality degradation. Hence, to test the proposed algorithm for the identification of classification accuracy, the MIT-BIH arrhythmia dataset is utilised.

RQ4: How proposed algorithm better than existing techniques?

The proposed 'AI-Dense Fit' model is very efficient and low-cost in classifying and predicting cardiac arrhythmia with a higher accuracy of 98.00% than classic classifiers and models. The proposed study provided an efficient dense neural network model with the new algorithm, AI-DenseFit.' The experimental execution with training and validation is accomplished on the most trusted MIT-BIH arrhythmia dataset and identifies precision, recall, and F1-score. The single heartbeat ECG classification for Normal, Supraventricular premature, Premature ventricular contraction, Fusion of ventricular, and Fusion of paced has been successfully carried out. Hence, the proposed research is very useful for medical experts in deciding the patient's treatment line. In future research, the proposed algorithm can be used as a plug-in for robotic cardiac surgery. However, we further optimised the proposed 'AI-DenseFit model and developed the 'Self-attention-AE' model to improve the accuracy of the 'AI-DenseFit model.

The system quickly predicts ECG signals by combining the Self-Attention Autoencoder with the TKF framework. It achieves 99.7% accuracy, 99.91% precision, and 99.86% recall. The research limitations identified in earlier literature are directly addressed by our findings.

With the fewest classification mistakes, the Self-Attention Autoencoder performed the best. Reconstruction greatly decreased errors through repeated execution during training and validation, allowing for precise arrhythmia prediction even for R-R peak evolution and single-pulse QRS complexes. Determining the best course of treatment for patients in clinical practice requires the timely and precise identification of such anomalies. According to comparative studies, the suggested

method performs better than the most recent systems in use. Thus, in addition to the suggested approach, further development is carried out in the direction of repeatedly denoising ECG signals through recurrent ECG signal reconstruction.

RQ5: How proposed research beneficial for healthcare professionals?

The proposed research is multifaceted and is beneficial for healthcare professionals in many ways. The proposed research can enable the more accurate classification of cardiac arrhythmia, even for a single heartbeat analysis. This facilitates doctors with easy identification of the ECG component affecting the overall heartbeat functioning.

Apart from this, the proposed system can be combined with Internet of Things (IoT) systems like wearable healthcare devices to analyse and alert to the state of a patient's cardiac arrhythmia. Further, the impact of PLI gets reduced, and clearer ECG recordings can be produced, which may reduce the manual ECG reading errors. After all, the visibility of physical ECG reports depends on printing device quality, ink impressions, and paper roll quality. Due to the proposed system, it is easy to increase the filtered visibility of the ECG report, and it is an eco-friendly option that indirectly contributes to the Sustainable Development Goal (SDG) of India.

As the proposed system is self-attention-based, automated cardiac surgery assistance can be provided with heart rhythm analysis monitoring. However, plug-in development is needed for the same.

RQ6: Which parameters are important for the classification of heart arrhythmia conditions?

This thesis discussed numerous factors influencing the classification of heart arrhythmia, including the major role of PLI, and the core technical parameters identified are algorithmic execution for filtering PLI. To handle PLI, the Tuned Kalman filter proved to be efficient by recurrent execution of the current state of the model by considering the previous state of the model, which eliminates the noise level of signal interference. Further, hyperparameter tuning is also important to analyse the dataset accurately. Epoch size matters to get an optimum accuracy during the classification of cardiac arrhythmia, as a large epoch size leads to degraded results, whereas a small epoch size leads to sluggish response. So, optimum epoch size is important for fast and accurate results.

Most importantly, in the case of a real-time study, the physical ECG reports need to be clear and loud before converting them to digital forms; otherwise, there is a possibility of wrong interpretation. The QRS complex and R-R interval analysis is very important during the study of cardiac arrhythmia classification.

9.2 Clinical Deployment Challenges and Practical Considerations

Although the proposed Self-Attention Autoencoder with Tuned Kalman Filter achieved excellent classification performance on the MIT-BIH arrhythmia dataset, several challenges must be addressed before its routine clinical deployment.

1. Clinical Validation

The proposed model has been evaluated on benchmark and real-time datasets; however, large-scale multicenter clinical validation is required before deployment in hospitals. The algorithm should be tested across diverse populations, age groups, ethnicities, and different ECG acquisition devices to ensure generalizability.

2. Regulatory Approval

AI-based medical diagnostic systems must comply with regulatory requirements before clinical use. Depending on the country, approvals from agencies such as the FDA (USA), CE (Europe), or the CDSCO (India) are necessary. Demonstrating safety, reliability, reproducibility, and risk assessment is essential.

3. Data Privacy and Security

ECG recordings contain sensitive patient information. Therefore,

- patient identity anonymisation,
- encrypted data transmission,
- secure cloud storage,
- compliance with healthcare privacy regulations

are mandatory before real-world deployment.

4. Integration with Hospital Infrastructure

The proposed system should be compatible with existing

- ECG machines,
- Hospital Information Systems (HIS),
- Electronic Health Records (EHR),
- Picture Archiving and Communication Systems (PACS),

to allow seamless clinical workflow without disrupting existing medical practice.

5. Real-Time Computational Requirements

Although the proposed model achieves high accuracy, practical deployment requires low-latency inference on embedded devices, smartphones, or wearable ECG monitors. Computational efficiency and memory optimisation remain important considerations.

6. Model Robustness

Real-world ECG signals are affected by

- motion artifacts,
- electrode displacement,
- baseline wander,
- muscle noise,
- device variability.

Future validation should evaluate robustness under these practical conditions.

7. Explainability of AI Decisions

Clinicians require transparent AI systems rather than black-box predictions. Future versions of the proposed framework may incorporate explainable AI techniques to highlight ECG segments or waveform features responsible for arrhythmia prediction, thereby improving clinician confidence.

8. Human-in-the-Loop Decision Making

The proposed model should function as a clinical decision support tool rather than replacing cardiologists. Final diagnosis and treatment decisions should remain under physician supervision.

9. Continuous Model Updating

Clinical practice evolves. Periodic retraining using newly collected ECG data is necessary to maintain diagnostic accuracy and adapt to changes in patient demographics and clinical protocols.

9.3 Generalizability to Multicentre Clinical Datasets

The proposed Self-Attention Autoencoder framework was evaluated using the MIT-BIH Arrhythmia Database together with the collected real-time ECG data. Although these datasets demonstrate the effectiveness of the proposed methodology, they may not fully represent the diversity encountered in routine clinical practice. ECG characteristics can vary across hospitals due to differences in patient demographics, disease prevalence, electrode placement, acquisition devices, sampling frequencies, and clinical protocols.

Therefore, before widespread clinical adoption, the proposed model should be validated using larger multicenter datasets collected from multiple healthcare institutions. Such validation would assess the robustness, reproducibility, and generalizability of the proposed algorithm under heterogeneous clinical conditions. The Tuned Kalman Filter and Self-Attention Autoencoder are designed to learn generalised ECG representations, which are expected to improve adaptability to diverse datasets; however, this hypothesis requires confirmation through prospective multicenter clinical studies.

Future work will focus on evaluating the proposed framework on larger multicenter ECG databases involving diverse populations, different recording equipment, and varying clinical environments to further establish clinical reliability and scalability. In addition to the benchmark MIT-BIH dataset, preliminary validation was performed

using real-time ECG data collected from a collaborating hospital. Although this provides initial evidence of practical applicability, the sample size remains limited and does not constitute a true multicenter evaluation. Therefore, further validation across multiple institutions with diverse patient populations is required before routine clinical deployment.

9.4 Future Scope

The proposed study focuses more on the improvement in the accuracy of cardiac arrhythmia classification. However, future research can be extended for robotic surgery assistance using the self-attention-based proposed system. During open-heart surgery, such systems can assist in avoiding sudden cardiac arrest situations, eventually avoiding life-threatening situations.

Research can also be extended using IoT wearable devices, which can monitor the state of R-R intervals and alert patients to stay calm. For patients with severe arrhythmia conditions, an extreme alert system can be developed, which can facilitate the patient's location identification using GPS and an automatic call to register cardiac ambulance services. In this scenario, the future telecardiology system can be set to generate an alert after consecutive risky beat identification out of QRS-complex and/or R-R intervals. A similar system can be developed for sports persons too, as many younger athletes are victims of sudden cardiac arrest incidents.

Technological developments in external monitoring devices and/or implantable loop recorders will significantly influence our approach to resuscitation and risk classification for sudden cardiac death (SCD). These monitors will not only be

used for continuous risk assessment, but as their localisation and transmission capabilities advance, they may also be incorporated into the emergency response system to enable the prompt deployment of emergency medical technicians if a potentially fatal ventricular arrhythmia is detected.

Early detection and treatment of AF will be necessary in the future to stop its progression to more medically resistant types and to lessen the negative effects of AF. Early implementation of therapies to maintain sinus rhythm may avoid or postpone AF-related morbidity and mortality. AF causes electrophysiological and anatomical alterations that further promote and sustain AF. As previously mentioned, advancements in monitoring technology will enable early detection of AF, and the proposed approach will assist in clarifying the function of potential precursor arrhythmias that may suggest vulnerability, such as atrial tachycardia and premature atrial beats. Overall, future systems need to identify the various scenarios, personalities, environments, and circumstances to develop more personalised systems to avoid life-threatening situations. It is important to save the lives of patients with fast-acting systems. Overall, the proposed Self-Attention Autoencoder framework demonstrates strong potential for clinical translation owing to its high classification accuracy and effective ECG denoising capability. However, successful deployment in routine healthcare requires extensive multicenter clinical validation, regulatory approval, secure patient data management, interoperability with existing hospital information systems, computational optimisation for real-time applications, and improved model interpretability. Addressing these challenges will facilitate the adoption of the proposed system as a reliable clinical decision support tool for early cardiac

arrhythmia diagnosis. The following points should also be considered for the future scope

1. Validation on Large Multicentre ECG Datasets

Future work will evaluate the proposed Self-Attention Autoencoder framework using large multicenter ECG datasets collected from multiple hospitals. Such validation will improve the robustness and generalizability of the model across different patient populations, ECG acquisition devices, and clinical environments.

2. Lightweight Deep Learning Model

The current model can be further optimised through model compression, pruning, and quantisation techniques to reduce computational complexity. This would enable deployment on wearable devices, smartphones, and embedded healthcare systems while maintaining high classification accuracy.

3. Explainable Artificial Intelligence (XAI)

Future research will integrate Explainable AI techniques, such as Grad-CAM, SHAP, or attention visualization, to identify the ECG waveform regions contributing to arrhythmia classification. This will enhance clinician trust and facilitate interpretation of AI-assisted diagnoses.

4. Adaptive Signal Denoising

Although the proposed Tuned Kalman Filter effectively removes ECG noise, future work may investigate adaptive filtering methods capable of dynamically adjusting filtering parameters under varying noise conditions, including motion artifacts and baseline wander encountered in ambulatory ECG recordings.

5. Federated Learning

Future versions of the proposed framework may employ federated learning, enabling collaborative model training across multiple hospitals without sharing patient data. This approach would improve model robustness while preserving patient privacy.

6. Multimodal Healthcare Analytics

The proposed ECG-based model can be extended by integrating additional physiological signals such as photoplethysmography (PPG), blood pressure, oxygen saturation, respiration, and clinical history to improve early diagnosis of complex cardiovascular disorders.

7. Real-Time Edge Deployment

Future research will focus on deploying the proposed framework on edge computing platforms and IoT-enabled wearable devices to achieve real-time arrhythmia monitoring with low latency and reduced power consumption.

8. Continuous Learning

The proposed model may be enhanced using continual learning techniques that allow periodic updates from newly acquired ECG data while preventing catastrophic forgetting, thereby improving long-term clinical performance.

9. Clinical Decision Support System

Future work will integrate the proposed framework into hospital Electronic Health Record (EHR) systems and Clinical Decision Support Systems (CDSS), enabling automated risk stratification and real-time clinician alerts.

9.5 Chapter Summary:

This chapter encapsulates the outcomes and contributions of the proposed ECG-based cardiac arrhythmia detection system. Rooted in the philosophy of preventive healthcare and inspired by ancient Indian wellness practices, the study presents a novel AI-driven approach combining a Tuned Kalman filter for denoising and a Self-Attention Autoencoder (Self-Attention-AE) for effective feature extraction and classification. It addresses critical research questions related to real-time data handling, classification accuracy, and the shortcomings of earlier models. The proposed AI-DenseFit model demonstrated superior performance, achieving a classification accuracy of 99.79%, along with high precision and recall, outperforming traditional ML methods such as Logistic Regression, SVM, and XGBoost.

The system shows strong utility in real-time healthcare, especially in post-COVID contexts where arrhythmia cases are on the rise. It facilitates accurate single-beat ECG classification, enabling early detection and intervention. Additionally, it highlights the impact of Yoga, OM chanting, and pranayama on improving heart health. The proposed system can also be integrated with IoT-based wearable devices and supports SDG goals by reducing dependency on printed ECG outputs.

Looking ahead, the Future Scope outlines potential expansions into robotic cardiac surgery assistance, IoT-enabled emergency alert systems with GPS tracking, and wearable solutions for athletes and high-risk individuals. The research paves the way for personalised, real-time telecardiology systems capable of predicting and

preventing life-threatening cardiac events through advanced AI and continuous monitoring technologies.

BIBLIOGRAPHY:

- [1] Dietrich, Isa, et al. "The diabetic foot as a proxy for cardiovascular events and mortality review." *Current Atherosclerosis Reports*, Springer, 19 (2017): 1-5.
- [2] Johansson, Saga, et al. "Mortality and morbidity trends after the first year in survivors of acute myocardial infarction: a systematic review." *BMC Cardiovascular Disorders*, Springer, 17 (2017): 1-8.
- [3] Vaes, Bert, et al. "Association between traditional cardiovascular risk factors and mortality in the oldest old: untangling the role of frailty." *BMC Geriatrics*, Springer, 17 (2017): 1-8.
- [4] Shivappa, Nitin, et al. "Inflammatory potential of diet and all-cause, cardiovascular, and cancer mortality in National Health and Nutrition Examination Survey III Study." *European journal of nutrition*, Springer, 56 (2017): 683-692.
- [5] Paquette, Martine, et al. "Polygenic risk score predicts prevalence of cardiovascular disease in patients with familial hypercholesterolemia." *Journal of Clinical Lipidology*, Elsevier, 11.3 (2017): 725-732.
- [6] Shrivastava, U., et al. "Obesity, diabetes and cardiovascular diseases in India: public health challenges." *Current diabetes reviews* 13.1 (2017): 65-80.
- [7] Arabasadi, Zeinab, et al. "Computer-aided decision making for heart disease detection using a hybrid neural network-Genetic algorithm." *Computer methods and programs in biomedicine*, Elsevier, 141 (2017): 19-26.

- [8] Novo, Jorge, et al. "Wivern: a web-based system enabling computer-aided diagnosis and interdisciplinary expert collaboration for vascular research." *Journal of Medical and Biological Engineering*, Springer, 37 (2017): 920-935.
- [9] Slomka, Piotr J., et al. "Cardiac imaging: working towards fully automated machine analysis & interpretation." *Expert review of medical devices* 14.3 (2017): 197-212.
- [10] Stein, Philipp, et al. "Impact of city police layperson education and equipment with automatic external defibrillators on patient outcome after out-of-hospital cardiac arrest." *Resuscitation*, Elsevier, 118 (2017): 27-34.
- [11] Chatterjee, Parag, Leandro J. Cymberknop, and Ricardo L. Armentano. "IoT-based decision support system for intelligent healthcare applied to cardiovascular diseases." *2017 7th International Conference on Communication Systems and Network Technologies (CSNT)*. IEEE, 2017.
- [12] Johnson, Kipp W., et al. "Artificial intelligence in cardiology." *Journal of the American College of Cardiology* 71.23 (2018): 2668-2679.
- [13] Dohare, Ashok Kumar, Vinod Kumar, and Ritesh Kumar. "Detection of myocardial infarction in 12-lead ECG using support vector machine." *Applied Soft Computing*, Elsevier, 64 (2018): 138-147.
- [14] Diker, Aykut, et al. "Intelligent system based on Genetic Algorithm and support vector machine for detection of myocardial infarction from ECG signals." *2018 26th Signal processing and communications applications conference (SIU)*. IEEE, 2018.

- [15] Yang, Weiyi, et al. "Automatic recognition of arrhythmia based on principal component analysis network and linear support vector machine." *Computers in biology and medicine*, Elsevier, 101 (2018): 22-32.
- [16] Sannino, Giovanna e Giuseppe De Pietro. "A deep learning approach for ECG-based heartbeat classification for arrhythmia detection." *Future Generation Computer Systems*, Elsevier, 86 (2018): 446-455.
- [17] Xia, Yufa, et al. "An automatic cardiac arrhythmia classification system with wearable electrocardiogram." *IEEE Access* 6 (2018): 16529-16538.
- [18] Anwar, Syed Muhammad, et al. "Arrhythmia classification of ECG signals using hybrid features." *Computational and mathematical methods in medicine* 2018.1 (2018): 1380348.
- [19] Singh, Shraddha, et al. "Classification of ECG arrhythmia using recurrent neural networks." *Procedia Computer Science* 132 (2018): 1290-1297.
- [20] Marinho, Leandro B., et al. "A novel electrocardiogram feature extraction approach for cardiac arrhythmia classification." *Future Generation Computer Systems* 97 (2019): 564-577.
- [21] Hannun, Awni Y., et al. "Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network." *Nature Medicine* 25.1 (2019): 65-69.
- [22] Singh, Namrata, and Pradeep Singh. "Cardiac arrhythmia classification using machine learning techniques." *Engineering Vibration, Communication and Information Processing: ICoEVCi 2018, India*. Springer Singapore, 2019.

- [23] Alarsan, Fajr Ibrahim, and Mamoon Younes. "Analysis and classification of heart diseases using heartbeat features and machine learning algorithms." *Journal of big data* 6.1 (2019): 1-15.
- [24] Dang, Hao, et al. "A novel deep arrhythmia-diagnosis network for atrial fibrillation classification using electrocardiogram signals." *Ieee Access* 7 (2019): 75577-75590.
- [25] Huang, Jingshan, et al. "ECG arrhythmia classification using STFT-based spectrogram and convolutional neural network." *IEEE Access* 7 (2019): 92871-92880.
- [26] Xu, Xiaowen, et al. "Adaptive motion artefact reduction based on empirical wavelet transformation and wavelet thresholding for the non-contact ECG monitoring systems." *Sensors* 19.13 (2019): 2916.
- [27] Qian, Chunqiang, Honghong Su, and Helong Yu. "Local means denoising of ECG signal." *Biomedical Signal Processing and Control* 53 (2019): 101571.
- [28] Hao, Huaqing, et al. "Multi-lead model-based ECG signal denoising by guided filter." *Engineering Applications of Artificial Intelligence* 79 (2019): 34-44.
- [29] Wang, Jilong, et al. "Adversarial de-noising of electrocardiogram." *Neurocomputing* 349 (2019): 212-224.
- [30] Manju, B. R., and M. R. Sneha. "ECG denoising using Wiener filter and Kalman filter." *Procedia Computer Science* 171 (2020): 273-281.
- [31] Gaamouri, Sabah, Mounir Bousbia-Salah, and Rachid Hamdi. "Performance study of neural network unscented Kalman filter for denoising ECG signal." *Proceedings of the 8th International Conference on Sciences of Electronics, Technologies of*

Information and Telecommunications (SETIT'18), Vol. 2. Springer International Publishing, 2020.

[32] Mukhopadhyay, Sourav Kumar, and Sridhar Krishnan. "A singular spectrum analysis-based model-free electrocardiogram denoising technique." *Computer Methods and Programs in Biomedicine* 188 (2020): 105304.

[33] Singh, Pratik, and Gayadhar Pradhan. "A new ECG denoising framework using generative adversarial network." *IEEE/ACM transactions on computational biology and bioinformatics* 18.2 (2020): 759-764.

[34] Andrade, Jason G., et al. "The 2020 Canadian Cardiovascular Society/Canadian Heart Rhythm Society comprehensive guidelines for the management of atrial fibrillation." *Canadian Journal of Cardiology* 36.12 (2020): 1847-1948.

[35] Kirchhof, Paulus, et al. "Early rhythm-control therapy in patients with atrial fibrillation." *New England Journal of Medicine* 383.14 (2020): 1305-1316.

[36] Firyulina, M. A., and I. L. Kashirina. "Classification of cardiac arrhythmia using machine learning techniques." *Journal of Physics: Conference Series*. Vol. 1479. No. 1. IOP Publishing, 2020.

[37] Gajda, Robert. "Is continuous ECG recording on heart rate monitors the most expected function by endurance athletes, coaches, and doctors." *Diagnostics* 10.11 (2020): 867.

[38] Sahoo, S., et al. "Machine learning approach to detect cardiac arrhythmias in ECG signals: A survey." *Irbm* 41.4 (2020): 185-194.

[39] Tisdale, James E., et al. "Drug-induced arrhythmias: a scientific statement from the American Heart Association." *Circulation* 142.15 (2020): e214-e233.

[40] Krisai, Philipp, et al. "Associations of symptoms and quality of life with outcomes in patients with atrial fibrillation." *Heart* 106.23 (2020): 1847-1852.

[41] Stempfel, Samuel, et al. "Symptoms and quality of life in patients with coexistent atrial fibrillation and atrial flutter." *IJC Heart & Vasculature*, Elsevier, 29 (2020): 100556.

[42] Disertori, M., et al. (2017). Myocardial fibrosis assessment by LGE is a powerful predictor of ventricular tachyarrhythmias in ischemic and non-ischemic cardiomyopathy.

[43] Cannavan, Priscila MS, et al. "Translation and Validation of the Arrhythmia-Specific Questionnaire in Tachycardia and Arrhythmia (ASTA) to the Brazilian Context: An Instrument Focusing on Arrhythmia Symptoms." *Cardiology Research and Practice* 2020.1 (2020): 1402916.

[44] Varroosis, Dimitrios, et al. "Cardiac arrhythmias in arterial hypertension." *The Journal of Clinical Hypertension* 22.8 (2020): 1371-1378.

[45] Feng, Tingting, et al. "Symptoms of anxiety and depression and risk of atrial fibrillation—The HUNT study." *International Journal of Cardiology*, Elsevier, 306 (2020): 95-100.

[46] Heo, Ran, et al. "Characteristics of symptom burden in atrial fibrillation with concomitant heart failure." *International Journal of Arrhythmia*, Springer, 21 (2020): 1-8.

- [47] Feeny, Albert K., et al. "Artificial intelligence and machine learning in arrhythmias and cardiac electrophysiology." *Circulation: Arrhythmia and Electrophysiology* 13.8 (2020): e007952.
- [48] Rizwan, Ali, et al. "A review on the state of the art in atrial fibrillation detection enabled by machine learning." *IEEE reviews in biomedical engineering* 14 (2020): 219-239.
- [49] Arsalan, Muhammad, Avik Santra, and Christoph Will. "Improved contactless heartbeat estimation in FMCW radar via Kalman filter tracking." *IEEE Sensors Letters* 4.5 (2020): 1-4.
- [50] Malghan, Pavan G., and Malaya Kumar Hota. "A review on ECG filtering techniques for rhythm analysis." *Research on Biomedical Engineering*, Springer, 36 (2020): 171-186.
- [51] Bae, Tae Wuk, Sang Hag Lee, and Kee Koo Kwon. "An adaptive median filter based on sampling rate for R-peak detection and major-arrhythmia analysis." *Sensors* 20.21 (2020): 6144.
- [52] Mazaheri, Vajihe, and Hamed Khodadadi. "Heart arrhythmia diagnosis based on the combination of morphological, frequency and nonlinear features of ECG signals and metaheuristic feature selection algorithm." *Expert Systems with Applications*, Elsevier, 161 (2020): 113697.
- [53] Jha, Chandan Kumar, and Maheshkumar H. Kolekar. "Cardiac arrhythmia classification using tunable Q-wavelet transform based features and support vector machine classifier." *Biomedical Signal Processing and Control* 59 (2020): 101875.

- [54] Bodile, Roshan M., and TVK Hanumantha Rao. "ECG Denoising Using Cubature Quadrature Kalman Filter Approach." 2020 IEEE India Council International Subsections Conference (INDISCON). IEEE, 2020.
- [55] Sun, Hongxiao, et al. "Prediction of arrhythmia after intervention in children with atrial septal defect based on random forest." *BMC paediatrics* 21.1 (2021): 280.
- [56] Yang, Ping, et al. "Ensemble of kernel extreme learning machine based random forest classifiers for automatic heartbeat classification." *Biomedical Signal Processing and Control*, Elsevier, 63 (2021): 102138.
- [57] Yadav, Samir S., and Shivajirao M. Jadhav. "Detection of common risk factors for diagnosis of cardiac arrhythmia using a machine learning algorithm." *Expert systems with applications*, Elsevier, 163 (2021): 113807.
- [58] Watanabe, Eiichi, et al. "Comparison among random forest, logistic regression, and existing clinical risk scores for predicting outcomes in patients with atrial fibrillation: A report from the J-RHYTHM registry." *Clinical Cardiology* 44.9 (2021): 1305-1315.
- [59] Essa, Ehab, and Xianghua Xie. "An ensemble of deep learning-based multi-models for ECG heartbeats arrhythmia classification." *IEEE Access* 9 (2021): 103452-103464.
- [60] Chang, Kuan-Cheng, et al. "Usefulness of machine learning-based detection and classification of cardiac arrhythmias with 12-lead electrocardiograms." *Canadian Journal of Cardiology* 37.1 (2021): 94-104.
- [61] Gupta, Aashuli, et al. "Prediction and classification of cardiac arrhythmia." *Sentimental Analysis and Deep Learning: Proceedings of ICSADL 2021*. Springer Singapore, 2022.

- [62] Xu, Yixian, et al. "Predicting ICU mortality in rheumatic heart disease: comparison of XGBoost and logistic regression." *Frontiers in Cardiovascular Medicine* 9 (2022): 847206.
- [63] Aggarwal, Ritu, Prajoy Podder, and Aditya Khamparia. "Ecg classification and analysis for heart disease prediction using xai-driven machine learning algorithms." *Biomedical data analysis and processing using explainable (XAI) and responsive artificial intelligence (RAI)*. Singapore: Springer Singapore, 2022. 91-103.
- [64] Shanmugavadivel, Kogilavani, et al. "Investigation of Applying Machine Learning and Hyperparameter Tuned Deep Learning Approaches for Arrhythmia Detection in ECG Images." *Computational and Mathematical Methods in Medicine* 2022.1 (2022): 8571970.
- [65] Li, Jiahao, et al. "Two-dimensional ECG-based cardiac arrhythmia classification using DSE-ResNet." *Scientific Reports* 12.1 (2022): 14485.
- [66] Ozcan, Mert, and Serhat Peker. "A classification and regression tree algorithm for heart disease modelling and prediction." *Healthcare Analytics, Elsevier*, 3 (2023): 100130.
- [67] Malakouti, Seyed Martin. "Heart disease classification based on ECG using machine learning models." *Biomedical Signal Processing and Control, Elsevier*, 84 (2023): 104796.
- [68] Kumar, Ashwani, et al. "Flamingo-optimisation-based deep convolutional neural network for IoT-based arrhythmia classification." *Sensors* 23.9 (2023): 4353.

- [69] Taher, Fatma, et al. "Cardiac Arrhythmia Disease Classifier Model Based on a Fuzzy Fusion Approach." *Computers Materials & Continua* 75.2 (2023): 4485.
- [70] Deepa, S. R., et al. "Precision Diagnostic Algorithm for Multisubtype Arrhythmia Classification." *2023 IEEE International Conference on Recent Advances in Systems Science and Engineering (RASSE)*. IEEE, 2023.
- [71] Sardana, H. K., R. Kanawade, and N. Dogra. "Photoplethysmograph based arrhythmia detection using morphological features." *Biomedical Signal Processing and Control, Elsevier*, 81 (2023): 104422.
- [72] Singh, Prateek, and Ambalika Sharma. "Attention-based convolutional denoising autoencoder for two-lead ECG denoising and arrhythmia classification." *IEEE Transactions on Instrumentation and Measurement*, 71 (2022): 1-10.
- [73] Venkatesh, N. Prasanna, R. Pradeep Kumar, Bala Chakravarthy Neelapu, Kunal Pal, and J. Sivaraman. "Automated atrial arrhythmia classification using 1D-CNN-BiLSTM: A deep network ensemble model." *Biomedical Signal Processing and Control* 97 (2024): 106703.
- [74] Singh, Prem Narayan, and Rajendra Prasad Mahapatra. "A novel deep learning approach for arrhythmia prediction on ECG classification using recurrent CNN with GWO." *International Journal of Information Technology, Springer*, 16.1 (2024): 577-585.
- [75] Singh, Madan, et al. "Revolutionising Arrhythmia Classification: Unleashing the Power of Machine Learning and Data Amplification for Precision Healthcare." *2024*

Sixth International Conference on Computational Intelligence and Communication Technologies (CCICT). IEEE, 2024.

[76] Sadeghi, Alireza, et al. "3DECG-Net: ECG fusion network for multi-label cardiac arrhythmia detection." *Computers in Biology and Medicine*, Elsevier, 182 (2024): 109126.

[77] Alamatsaz, Negin, et al. "A lightweight hybrid CNN-LSTM explainable model for ECG-based arrhythmia detection." *Biomedical Signal Processing and Control*, Elsevier, 90 (2024): 105884.

[78] Lee, Shuenn-Yuh, et al. "AI Accelerator with Ultralightweight Time-Period CNN-Based Model for Arrhythmia Classification." *IEEE transactions on biomedical circuits and systems* (2024).

[79] Guo, Rong-Xin, et al. "Application of artificial intelligence in the diagnosis and treatment of cardiac arrhythmia." *Pacing and Clinical Electrophysiology* (2024).

[80] Lee, Shuenn-Yuh, Wei-Cheng Tseng, and Ju-Yi Chen. "An Ultra-Lightweight Time Period CNN Based Model with AI Accelerator Design for Arrhythmia Classification." *2024 IEEE International Symposium on Circuits and Systems (ISCAS)*. IEEE, 2024.

[81] Fira, Monica, Hariton-Nicolae Costin, and Liviu Goras. "Prediction and Detection of Ventricular Fibrillation Using Complex Features and AI-Based Classification." *Applied Sciences* 14.7 (2024): 3050.

- [82] Supriya, M. S., and K. S. Arvind. "Advancements in Arrhythmia Classification: A Comprehensive Survey of AI Techniques." *International Conference On Innovative Computing and Communication*. Singapore: Springer Nature Singapore, 2024.
- [83] Vásquez-Iturralde, Fernando, et al. "Automatic Classification of Cardiac Arrhythmias using Deep Learning Techniques: A Systematic Review." *IEEE Access* (2024).
- [84] Khatar, Zakaria, Dounia Bentaleb, and Saadia Drissi. "Bayesian Methods for Multi-Objective Optimization of Hybrid Numerical Filters in ECG Signal Processing for Accurate Arrhythmia Classification." *Statistics, Optimization & Information Computing* 13.3 (2025): 993-1012.
- [85] Hesar, Hamed Danandeh, and Amin Danandeh Hesar. "Adaptive augmented cubature Kalman filter/smother for ECG denoising." *Biomedical Engineering Letters* 14.4 (2024): 689-705.
- [86] Elouaham, Samir, et al. "Empirical wavelet transform based ecg signal filtering method." *Journal of Electrical and Computer Engineering* 2024.1 (2024): 9050909.
- [87] Bai, Xiangyun, et al. "A hybrid deep learning network for automatic diagnosis of cardiac arrhythmia based on 12-lead ECG." *Scientific Reports* 14.1 (2024): 24441.
- [88] Curtis, Aaron D., Alexander J. Mertens, and Hai-Ling Margaret Cheng. "A predictive signal model for dynamic cardiac magnetic resonance imaging." *Scientific Reports* 13.1 (2023): 10296.

- [89] Kim, Namho, et al. "WavelNet: A novel convolutional neural network architecture for arrhythmia classification from electrocardiograms." *Computer Methods and Programs in Biomedicine* 231 (2023): 107375.
- [90] Gon, Anusaka, and Atin Mukherjee. "FPGA-based low-cost architecture for R-peak detection and heart-rate calculation using lifting-based discrete wavelet transform." *Circuits, Systems, and Signal Processing* 42.1 (2023): 580-600.
- [91] Rahman, Md Moklesur, et al. "Residual-attention deep learning model for atrial fibrillation detection from Holter recordings." *Journal of Electrocardiology*, 89, Elsevier, (2025): 153876.
- [92] Rodriguez, Mario Padilla, and Mohamed Nafea. "Hierarchical Attention Network for Interpretable ECG-based Heart Disease Classification." *arXiv preprint arXiv:2504.03703* (2025).
- [93] Islam, Md Rabiul, et al. "Cat-net: Convolution, attention, and transformer-based network for single-lead ECG arrhythmia classification." *Biomedical Signal Processing and Control* 93 (2024): 106211.
- [94] Jiang, Rucheng, et al. "A dual-branch convolutional neural network with domain-informed attention for arrhythmia classification of 12-lead electrocardiograms." *Engineering Applications of Artificial Intelligence, Elsevier*, 139 (2025): 109480.
- [95] Degachi, Oumayma, and Kais Ouni. "An attention-augmented bidirectional LSTM-based encoder-decoder architecture for electrocardiogram heartbeat

classification." *Transactions of the Institute of Measurement and Control* (2025): 01423312241252459.

[96] Berrahou, Nadia, et al. "Synergistic Approaches for Accurate Arrhythmia Prediction: A Hybrid AI Model Integrating Higuchi Dimensional Fractal, RR-intervals and Attention-based Convolutional Neural Network in ECG Signal Analysis." *Statistics, Optimisation & Information Computing* 13.2 (2025): 547-567.

[97] Msigwa, Godwin, Ester Ntambala, and Jaeseok Yun. "Enhancing atrial fibrillation classification from single-lead electrocardiogram signals using attention-based networks and generative adversarial networks with density-based clustering." *Engineering Applications of Artificial Intelligence* 133 (2024): 108607.

[98] Ghasemi, Ali, and Farzin Shama. "Extraction and noise reduction of the fetal electrocardiogram using Savitzky-Golay and adaptive filters." *Signal Processing and Renewable Energy* 8.4 (2024): 1-12.

[99] Elouaham, Samir, et al. "Empirical wavelet transform-based ECG signal filtering method." *Journal of Electrical and Computer Engineering* 2024.1 (2024): 9050909.

[100] De Vries, I. R., et al. "Deep learning for sparse domain Kalman filtering with applications on ECG denoising and motility estimation." *IEEE Transactions on Biomedical Engineering* (2024).

[101] Daydulo, Yared Daniel, Bheema Lingaiah Thamineni, and Ahmed Ali Dawud. "Cardiac arrhythmia detection using a deep learning approach and time frequency representation of ECG signals." *BMC Medical Informatics and Decision Making* 23.1 (2023): 232.

- [102] Batteau, Allen, and Christine Z. Miller. "The Enchantment of Technology." *Tools, Totems, and Totalities: The Modern Construction of Hegemonic Technology*. Singapore: Springer Nature Singapore, 2025. 185-196.
- [103] Sebag, Mikael D. "A Definition of Enchantment": A New Approach to the Analysis of Magic Systems in Fantasy Games." *Games and Culture* (2025): 15554120241310925.
- [104] Rahman, Atta Ur, et al. "Enhancing heart disease prediction using a self-attention-based transformer model." *Scientific Reports* 14.1 (2024): 514.
- [105] Li, Li, Xi Chen, and Sanjun Hu. "Application of an end-to-end model with self-attention mechanism in cardiac disease prediction." *Frontiers in Physiology* 14 (2024): 1308774.
- [106] Chen, Siyuan, et al. "A novel method of swin transformer with time-frequency characteristics for ECG-based arrhythmia detection." *Frontiers in Cardiovascular Medicine* 11 (2024): 1401143.
- [107] Edder, Aymane, et al. "Self-Attention-Driven ECG Denoising: A Transformer-Based Approach for Robust Cardiac Signal Enhancement." (2025).
- [108] Zhu, Xiangqian, et al. "Self-supervised inter–intra period-aware ECG representation learning for detecting atrial fibrillation." *Biomedical Signal Processing and Control* 100 (2025): 106939.
- [109] Dong, Yanfang, et al. "An arrhythmia classification model based on vision transformer with deformable attention." *Micromachines* 14.6 (2023): 1155.

[110] Kuila, Sumanta, Namrata Dhanda, and Subhankar Joardar. "ECG signal classification to detect heart arrhythmia using ELM and CNN." *Multimedia Tools and Applications* 82.19 (2023): 29857-29881.

[111] Khan RH, Miah J, Nipun SA, Islam M. "A Comparative Study of Machine Learning classifiers to analyze the Precision of Myocardial Infarction prediction." In 2023 IEEE 13th Annual Computing and Communication Workshop and Conference (CCWC), IEEE, 2023, pp. 0949-0954.

[112] Dhyani S, Kumar A, Choudhury S. "Analysis of ECG-based arrhythmia detection system using machine learning." *MethodsX*, vol. 10, 2023 , p.102195.

[113] Ramkumar M, Alagarsamy M, Balakumar A, Pradeep S. "Ensemble classifier fostered detection of arrhythmia using ECG data." *Medical & Biological Engineering & Computing*, vol. 61, 2023 pp.2453-66.

[114] Bhukya R, Shastri R, Chandurkar SS, Subudhi S, Suganthi D, Sekhar MS. "Detection and classification of cardiac arrhythmia using artificial intelligence." *International Journal of System Assurance Engineering and Management*, vol. 26, 2023, pp. 1-8.

[115] Singhal S, Kumar M. "A systematic review on artificial intelligence-based techniques for diagnosis of cardiovascular arrhythmia diseases: challenges and opportunities." *Archives of Computational Methods in Engineering* vol. 30, 2023, pp. 865-88.

- [116] Khafaga DS, Alhussan AA, Abdelhamid AA, Ibrahim A, Saber M, El-Kenawy ES. “Dipper Throated Algorithm for Feature Selection and Classification in Electrocardiogram.” *Comput. Syst. Sci. Eng.*, vol. 45, 2023, pp. 1469-82.
- [117] Kıymaç E, Kaya Y. “A novel automated CNN arrhythmia classifier with memory-enhanced artificial hummingbird algorithm.” *Expert Systems with Applications*, vol. 213, 2023, p. 119162.
- [118] Phukan N, Manikandan MS, Pachori RB. “Afibri-net: A lightweight convolution neural network based atrial fibrillation detector.” *IEEE Transactions on Circuits and Systems I*, vol. 69, 2023, pp. 252-265.
- [119] Salehi A, Balasubramanian M. “DDCNet: Deep dilated convolutional neural network for dense prediction.” *Neurocomputing*, Elsevier, vol. 523, 2023, pp. 116-129.
- [120] Liu Y, Zhang J. “A lightweight convolutional neural network based on dense connection for open-pit coal mine service identification using the edge-cloud architecture.” *Journal of Cloud Computing*, vol. 12, 2023, p. 32.
- [121] Talukder MA, Layek MA, Kazi M, Uddin MA, Aryal S. “Empowering COVID-19 detection: Optimising performance through fine-tuned EfficientNet deep learning architecture.” *Computers in Biology and Medicine*, vol. 168, 2024, p. 107789.
- [122] Ameet Shah Dhanpratap Singh “Electrocardiogram analysis for cardiac arrhythmia classification and prediction through self-attention-based autoencoder” March 2025 *Scientific Reports* 15[1] DOI: 10.1038/s41598-025-93906-5.
- [123] Ameet Shah Dhanpratap Singh “Cognitive Cardiovascular Disease Prediction Using ECG-Crown Auto Encoder Neural Network for ECG Time Series Signals” 2024
-

[124] Ameet Shah Dhanpratap Singh “Efficient Application of Kalman Filter for Enhancement of ECG Signal Visibility by Denoising Power Line Interference”
Efficient Application of Kalman Filter for Enhancement of ECG Signal Visibility by Denoising Power Line Interference DOI: 10.1109/ICPCN63822.2024.00110

[125]Drezner, J. A., et al. (2020). *Is Continuous ECG Recording on Heart Rate Monitors the Most Expected Function by Endurance Athletes, Coaches, and Doctors* Diagnostics, 10(11), 867.

[126] Yufa Xia et al., "An Automatic Cardiac Arrhythmia Classification System with Wearable Electrocardiogram," IEEE Access, 2018. (Uses Stacked Denoising Autoencoder (SDAE) for wearable ECG classification.)

[127] Raymond W. Sy et al. Smartphone applications for cardiac rhythm monitoring. *Journal of Arrhythmia*, 2019.

[128] Sonia Sultan et al Smartphone-Based Arrhythmia Monitoring: A Review. *Heart Rhythm O2*, 2021.

[129] Pan, J., & Tompkins, W. J. (1985). *A Real-Time QRS Detection Algorithm*. IEEE Transactions on Biomedical Engineering, 32(3), 230–236.

[130] CVG Cares, "Cardiac Arrhythmia (Normal heart vs. Arrhythmia)," [Online]. Available: CVG Cares – Causes and Treatment for Heart Arrhythmia. Accessed: Aug. 5, 2026.

[131] Kotte, S., & Dabbakuti, J. R. K. (2020). Methods for removal of artifacts from EEG signal: A review. *Journal of Physics: Conference Series*, 1706(1), 012093.

[132] Shunmugavel, G., Suriyan, K., & Arumugam, J. (2024). Magnetic resonance imaging-based brain tumour extraction, segmentation and detection using convolutional neural network and VGC 16 model. *American Journal of Clinical Oncology*, 47(7), 339–349. doi.org

[133] J. Gilles, "Empirical Wavelet Transform," *IEEE Transactions on Signal Processing*, vol. 61, no. 16, pp. 3999–4010, Aug. 2013, doi: 10.1109/TSP.2013.2265222.

[134] Zeebaree, Diyar & Abdulazeez, Adnan & Abdullrhman, Lozan & Hasan, Dathar & Kareem, Omar. (2021). The Prediction Process Based on Deep Recurrent Neural Networks: A Review. *Asian Journal of Research in Computer Science*. 29-45. 10.9734/AJRCOS/2021/v11i230259.

RESEARCH SURVEY

Research Title: A Novel Approach to Classify Heart Arrhythmia Using Deep Learning

This is a survey for patients and medical professionals.

Your feedback is anonymous. Filling in the survey should take you a maximum of 5-10 minutes.

Your responses will help us identify the usability of the proposed research.

How long have you been associated with the medical field?

1 to 3 years

3+ years

☐
☐

Scale	Extremel y dissatisfi ed	Dissatisf ied	Neutral	Satisfied	Extremel y satisfied
Your overall health condition	☐	☐	☐	☐	☐
I am diagnosed with heart arrhythmia and satisfied with the treatment	☐	☐	☐	☐	☐
I visited more than 2 doctors to assist me with my heart problems	☐	☐	☐	☐	☐
My ECG recordings showing different readings with different diagnosis centres, and cannot be able to know the exact state of my heart disease	☐	☐	☐	☐	☐
Chanting of 'OM' gives positive ECG results	☐	☐	☐	☐	☐
Practicing yoga-pranayam gives good ECG results	☐	☐	☐	☐	☐
The work-life balance causing higher stress level and consequently the heart arrhythmia diagnosed	☐	☐	☐	☐	☐

Smoking is the cause of my heart blockages which leads to heart arrhythmia as per the opinion of doctors	☐	☐	☐	☐	☐
I appreciate the quick and accurate heart disease prediction using your system	☐	☐	☐	☐	☐
I prefer natural healing for the heart arrhythmia problem	☐	☐	☐	☐	☐
For Doctors					
As a doctor, there is a need for an automated technique to identify heart problems accurately and swiftly	☐	☐	☐	☐	☐
The ECG signals are not readable in the ECG report and are with unclear QRS complex.	☐	☐	☐	☐	☐
Natural healing with 'OM' chanting impacts positively for patients	☐	☐	☐	☐	☐
Artificial intelligence can be a specific solution for ECG signal analysis	☐	☐	☐	☐	☐
The demonstration shown by the research scholar is a most prominent solution for the identification of single heartbeat analysis, and so it is helpful for the correct diagnosis of disease.	☐	☐	☐	☐	☐
The system developed by the research scholar can be used by doctors.	☐	☐	☐	☐	☐
The accuracy of the work is higher.	☐	☐	☐	☐	☐
Visibility of results is higher for the decision of the line of action.	☐	☐	☐	☐	☐

PROJECT TESTING REPORT



Near Gigaspace, Vimannagar, Pune
Contact No : 020- 65237076
E-mail : info@xpertechnologies.com, sales@xpertechnologies.com
Website: www.xpertechnologies.com

Ref: XT/2024/3/21

Date: 27th March 2024

To
Mr. Dhanpratap Singh
Professor
Lovely Professor University
Punjab.

Project Testing Certificate

Dear Sir,

We understand that Mr. Ameet Shah has enrolled with your esteemed university as a Research Scholar under the enrollment NO: 42000504 in the department of Computer Science Engineering under the guidance of Dr. Dhanpratap Singh. We tested his research project for the feasibility and applicability. We are happy to inform you that your project testing is successful and results are optimum.

Test Unit Manager: Mrs. Shruti P.

Xpert Technologies
Address: Giga Space,
Pune-Nagar Road, Vimannagar,
Pune, Maharashtra 411015

Thanking You,



DOCTOR RECOMMENDATION LETTER

BAKHTAR HOSPITAL

ICCU & CARDIAC CLINIC



DR. VIJAY BAKHTAR

M.D. (Nag.), F.I.C.A. (USA), M.C.C.P. (Delhi), M.B.B.S. (Nag.)

Consultant Cardiologist & Physician

Date: 09-04-2023

Dr. Vijay Bakhtar

Cardiologist

Bakhtar Cardiac Hospital

Rajpeth

Amravati, Maharashtra

Email - bakhtarhospital11@gmail.com

Ameet Shah (Research Scholar Reg:420000504)

Research Title: A Novel Approach to Classify Heart Arrhythmia using deep learning

Lovely Professional University

Punjab Phagwara, India

Dear Ameet Shah,

Subject: Providing of ECG Dataset for Research Purposes

To Whomsoever it may concern

I hope this letter finds you well.

As per your request and in compliance with the ethical guidelines, I am providing you with the requested electrocardiogram (ECG) data for your research study titled “: **A Novel Approach to Classify Heart Arrhythmia using deep learning**”. The ECG data included in this package has been anonymized to ensure the confidentiality and privacy of the patients involved.

The data set comprises ECG recordings from number of patients, collected during the period of 2023-2024. Each recording has been thoroughly reviewed and verified for accuracy.

Please be reminded that this data is provided strictly for research purposes under the conditions outlined in the data-sharing agreement between **Bakhtar Cardiac Hospital** and to research Scholar **Mr. Ameet Shah**. We trust that you will handle this data responsibly and ensure its security and confidentiality.

Should you require any additional information or further clarification regarding the data provided, please do not hesitate to contact me.

Thank you for your collaboration, and I look forward to the outcomes of your research.

Best regards,

Dr. Vijay Bakhtar

Cardiologist

Bakhtar Cardiac Hospital



Bakhtar Hospital
Near Ice Factory, Rajapeth
Amravati
☎ 2677466, 2651049

Near Ice Factory, Rajapeth, Amravati.
Tel : 91-721-2677466, 2678062
E-mail : vijay_bakhtar@rediffmail.com

(Reg. No. : 54872)

LIST OF PUBLICATION

1. Ameet Shah, Dr Dhanpratap Singh “Denoising of Power Line interference at Negative SNR Contaminated Electrocardiogram signal using Kalman Filter”- Journal of Harbin Engineering University, ISSN: 1006-7043, Vol 44, No. 9, September 2023.
2. Ameet Shah, Dr Dhanpratap Singh “A survey of Heart Disease Prediction Using Deep Learning Methods”, Book Chapter: on Data Science and Intelligent Computing Techniques-Computing & Intelligent System, SCRS, India-2023
3. Ameet Shah, Dr Dhanpratap Singh “Efficient Application of Kalman Filter for Enhancement of ECG Signal Visibility by Denoising Power Line Interference” 5th International Conference on Image Processing and Capsule Networks- (ICICN 2024)-Nepal.
4. Ameet Shah , Dr Dhanpratap Singh, “Cognitive Cardiovascular Disease Prediction Using ECG-Crown Auto Encoder Neural Network for ECG Time Series Signals” 8th International Conference on Computing Communication Control & Automation-ICCUBEA-2024-Pune.
5. Ameet Shah, Dr Dhanpratap Singh, “Electrocardiogram analysis for cardiac arrhythmia classification and prediction through self-attention-based autoencoder”, Scientific Reports <https://doi.org/10.1038/s41598-025-93906-5> - 2025.