DEVELOPMENT OF AN INTELLIGENT HYBRID INFERENCE SYSTEM FOR MONITORING OF HEART DISEASE

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By

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2026

DECLARATION

I, hereby declared that the presented work in the thesis entitled ***“Development of an Intelligent Hybrid Inference System for Monitoring of Heart Disease”*** in fulfilment of degree of Doctor of Philosophy (Ph. D.) is the outcome of research work carried out by me under the supervision of Dr Dalwinder Singh, working as Associate Professor in the Department of Computer Science and Engineering of Lovely Professional University, Punjab, India. In keeping with 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 full to any other University or Institute for the award of any degree

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CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled ***“Development of an Intelligent Hybrid Inference System for Monitoring of Heart Disease”*** submitted in fulfilment of the requirement for the award of degree of Doctor of Philosophy (Ph.D.) in the Computer Science and Engineering, is a research work carried out by Janpreet Singh, reg. no 42200106 , is a bonafide record of his/her 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.

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Abstract

Being chronic and deteriorating, heart failure is a condition that persists over time. Heart damage can develop over time as a result of renal illness, diabetes, excessive blood pressure, and other endocrine disorders as well as cardiac problems. Initial compensatory mechanisms are developed by the organ, but as time goes on, the heart muscles sustain greater harm as a result of these attempts to cope with a growing strain. The walls of the heart's chambers may narrow as a result of compensatory stretching required to pump more forcefully, or they might thicken as the heart's muscle mass increases and adds to the force available. Because of how quickly and widely heart disease is spreading throughout the world, prevention is crucial. Regardless of where they are from, people should follow certain broad guidelines for primary preventive care. In accordance with regional recommendations released by regional professional medical authorities, a nutritious, regular and healthy diet, examination of disease and adequate treatment for illness should be followed as they are linked with high risk of heart disease, such as hyperlipidemia, hypertension and diabetes. According to established recommendations, those at high risk may be considered for common drugs like aspirin & statins. Secondary prevention is necessary for people with previous heart disease, and effective medications that have been shown to stop future incidents from happening are also recommended in addition to lifestyle improvements.

The monitoring of any disease at its introductory phase is always helpful for the patients as well as doctors to prevent the severe conditions of that particular disease. As the last stage of any disease is life threatening, and the probability of saving the patient is also low at that point. Similarly, heart disease is a deadly disease having high death rates due to the inaccessibility of detecting, monitoring and diagnosing patients at the initial phase. Machine learning-based expert systems assist doctors in beating this issue and make them capable of identifying and treating the disease automatically in the initial stages. These models utilize a rule based inference engine and fuzzy values to diagnose the suffering individuals. It is a very difficult task to predict if a patient suffering from heart failure will survive and assist the doctors in making accurate decisions related to the survival of an individual.

Proper care of a heart failure patient can only be done if the doctor has the necessary experience in the same domain. Additionally, the numerous linked factors to this disease make the diagnosis more challenging. Uncertainty arises from several factors, including

limits in the diagnostic technique, the presence of missing data, erroneous patient attributes, and the incapacity of medical practitioners to define the effects and causes of the condition. Hence, to remove this uncertainty in data and help the doctors in the prediction of heart failure, several authors presented and introduced new models. These models use machine learning algorithms which assist in the accurate diagnosis of the disease and in the extraction of correct data features from the patient. Smart devices and mobile technologies are widely utilized in the domain of health and have a major influence on people’s health worldwide. The numerous benefits of such approaches are extensively being used by various health professionals, which lead to a significant enhancement in the healthcare sector.

Machine learning techniques are successfully utilized in the creation and implementation of a concurrent health monitoring system that relies on ML technology. Machine learning is derived from knowledge, which imparts it with intelligence. Relying on human input can lead to failure. Hence, to achieve full immunity and adaptability to human fallibility, a system necessitates the assistance of machine learning. Algorithms in an integrated environment efficiently correct human errors using a feedback technique that optimizes the process. Machine learning algorithms analyze and identify patterns from past behaviour to provide assistance and predict future events and behaviour. These devices also aid in the early detection of heart failure, allowing patients to receive successful treatment before their condition deteriorates. In the healthcare system, the most crucial and vital issue is the procedure of heart disease diagnosis as the patient's life is only dependent on it, and it can reduce the disease at a particular level. However, in many cases, the selected procedure results in wrong and unexpected results or even lead to a patient’s death. Hence, the most challenging task in the medical domain is a diagnosis of heart disease done by medical professionals. In this technical era, the role of artificial intelligence in the healthcare system is considerable and appraisable. These days, people are preoccupied with their everyday tasks, paying close attention to their work and other obligations while putting their health on the back burner. A growing number of individuals fall ill every day as a result of their hectic lifestyle and disrespect for their health. Hence, the majority of the population across the world is affected by heart disease. Heart disease is one of the major causes of death globally, and early detection and monitoring are critical for effective treatment. Moreover, the use of machine learning is increasing quickly all around the world, particularly in the healthcare industry. Therefore, intelligent models can be developed or introduced by using machine learning approaches that predict the health of a patient’s heart from its risk factors.

Therefore, numerous papers exist that provide insight into the deployment and advancement of medical diagnostic systems. These systems utilize various machine learning techniques to predict heart failure. The primary objective of the paper is to statistically examine the research effort undertaken by different authors on the creation of inference systems utilizing machine learning. This study also examines other literature reviews that discuss specific methodologies and systems, as well as research publications that detail the implementation of these models. Various criteria, such as the study objective, publication year, research gap assessment, and paper findings, are employed to distinguish between the papers under consideration. Furthermore, the main aim of this conducted work is to review these proposed systems, which use machine learning techniques for the diagnosis of heart failure. The considered models are compared on the basis of their classification accuracy. The model which has the highest accuracy of classification is rewarded as a superior system to diagnose heart failure.

The main focus of this research is to develop or implement a model which uses the major symptoms of heart disease and detects the disease at its early stage. Therefore, the primary responsibility of the proposed model is to detect and monitor heart disease, and after that, the doctor will make a wise decision about treatment according to the outcome provided by the model. These models utilize a rule-based inference engine and fuzzy values to diagnose the suffering individuals. Moreover, the accurate medication dosage and recommendations provided to the patient are only dependent on the decision or result of this proposed model. Hence, it is essential to make a model that has maximum classification accuracy or minimum errors. The experimental results of this research work indicated that the developed model for the diagnosis of heart diseases achieves maximum accuracy and better performance in figuring out the correct risk levels of heart diseases.

Therefore, this study introduced a model which has the capability to monitor heart disease by using a hybrid methodology of machine learning, i.e. neuro fuzzy approach. In the developed intelligent hybrid inference system, there are a total of seven input variables utilized to classify the disease into different stages. The system generates the output, which provides the three different stages or levels of the disease. Moreover, according to this generated outcome, professional doctors of the heart can make a wise decision for the patient and also can choose the best procedure for the treatment corresponding to the disease's stage. The k-fold cross validation method is utilized to do the partitioning of the dataset and for testing purposes. The performance of the system is also calculated, and according to those results, the presented inference model accurately forecasts the stage of the heart disease from which a patient is suffering with an accuracy of 98.90 percent.

This study presents a comparative study in which models are proposed using fuzzy logic and hybrid systems and also their performances are compared with each other as well as existing models. The comparison is made by considering the classification accuracy of each model. The model which has the highest percentage of accuracy is considered as the most accurate model for the monitoring of heart disease. According to the results, it is found that the neuro fuzzy methodology assists in implementing an intelligent model which has 98.90 percent classification accuracy and also outperforms other existing models.

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Keywords

Artificial intelligence, healthcare, machine learning, heart disease, medical diagnostic system, neuro fuzzy inference system, medical expert system, Fuzzy expert system, statistical review, Comprehensive review.

CHAPTER 1: INTRODUCTION

1.1. About Heart Diseases

Heart failure (HF) is a clinical condition caused by anomalies in the basic functioning of the myocardium, leading to difficulties in ventricular filling and blood ejection [1]. The primary cause of heart failure is often the decreased functionality of the left ventricular myocardium. However, impairments in the heart valves, endocardium, myocardium, pericardium, or great vessels, either singly or in combination, can also cause heart failure. Heart failure can happen due to different problems in the body, such as genetic changes, faster cell death, unusual growth of tissue around the heart, irregular calcium movement in heart cells, increased signals from the nervous system and hormones, changes in the heart's shape, issues from reduced blood flow, and extra pressure on the heart. In the modern world, heart-related issues are quite prevalent [3]. The primary cause of increased heart failure risk is the accumulation of excess cholesterol in the blood vessels and arteries [4], [5]. The patient faces several challenges as a result, including depression, trouble sleeping, dyspnea, chest pain, and fatigue [6], [7]. Additionally, these body conditions also increase the risk of stroke and heart attack.

Research reveals that Hong Kong, Japan, and France have the lowest death rates from heart failure. Meanwhile, the countries having the highest number of deaths due to heart attacks are Africa and India. The percentage of deaths in these two nations due to this disorder is thirty-four percent and twenty-three percent, respectively [8]. Additionally, the estimated deaths due to heart attacks each year are 12M all over the world, as reported by W.H.O. [9]. Due to excessive alcohol, tobacco, and cigarette use, this chronic condition has been a problem in both developed and developing nations for the past forty years [10]. There are several factors, such as smoking, alcohol use, family history, increased blood sugar, high cholesterol levels, hypertension, obesity, age, and gender, which contribute to an increase in the probability of having heart disease [11], [12], [13]. Other risks include disturbed sleep due to technology use, changes in routine or diet, stress from inactivity or lack of exercise, and tension from overwork and underemployment due to industrialization

[14], [15]. Furthermore, the major chronic diseases of the heart in patients have been brought in by the huge change in attitudes like narcissism, greed, egoism, and lifestyle change [16].

Heart failure affects approximately 26 million individuals worldwide, and its prevalence is increasing [17]. The expenses associated with heart failure healthcare are substantial and are expected to increase significantly due to the aging population. Despite significant advancements in medicine and prevention, the quality of life remains low, and there have been substantial rates of death and illness. Geographic variations in the rates of morbidity, mortality, incidence, and prevalence among heart failure patients have been observed due to different causes and clinical characteristics [18]. In contrast to Europe, there has been a lack of substantial study performed to investigate the impact of heart failure in developing countries such as India. This has resulted in an incomplete understanding of the epidemiology of heart failure in these nations. Practicing internists and cardiologists are well aware of the magnitude of this burden, considering that India is home to 16% of the world's population and bears 25% of the burden of coronary heart disease. Furthermore, it is worth noting that there are currently 120 million persons in this country who are afflicted with hypertension, along with a considerable number of individuals who have RHD [19].

Therefore, heart disorders are the primary cause of a substantial number of deaths worldwide [20]. The presence of irregular pulse rate, diabetes, excessive cholesterol levels, and hypertension are contributory factors that complicate the prediction of cardiovascular illnesses [21]. Furthermore, the symptoms of various diseases also differ depending on the gender of an individual. Research indicates that men with heart disease are more likely to experience chest pain, while women with the same condition are more likely to experience symptoms such as shortness of breath, extreme exhaustion, and nausea, rather than chest discomfort [22]. Various writers and academics have established a range of approaches to predict this lethal illness. Nevertheless, accurately predicting this disease at its initial stage is challenging due to various elements that impact it, including precision, time required for execution, and the intricacy of the approach [23]. However, if a method can accurately forecast it at an early stage, then prompt diagnosis and treatment can potentially prevent a substantial percentage of patient fatalities [24], [25]. Figure 1 demonstrated the difference between a normal heart and heart failure of a human.

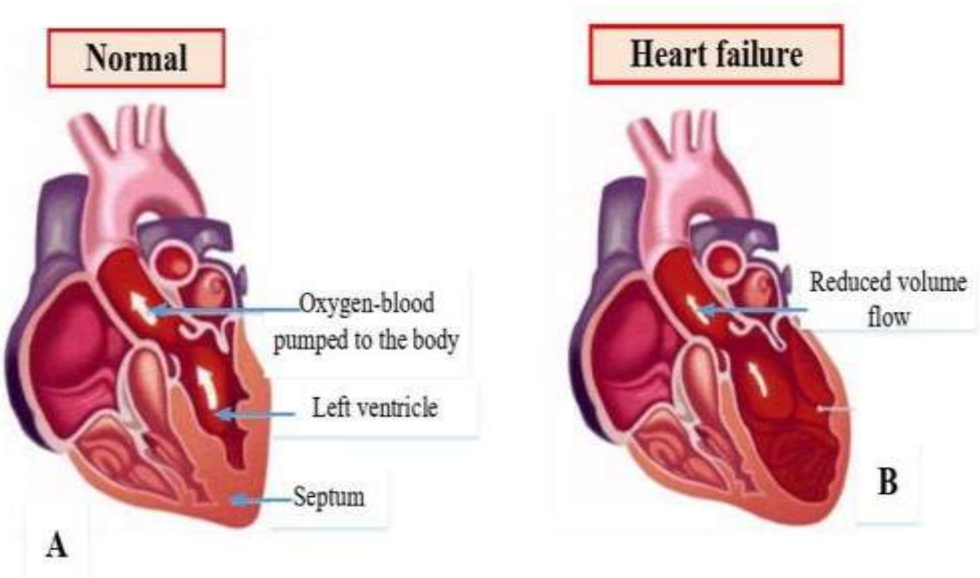

Figure 1: (A) Normal heart (B) Heart Failure [26]

Heart disease is the leading cause of mortality worldwide, responsible for approximately 18 million deaths annually, as reported by the World Health Organization. Cardiovascular diseases (CVD) encompass a range of conditions that affect the heart and blood vessels, including coronary artery disease, heart failure, and arrhythmias. Due to the high prevalence of these conditions, there is an urgent need for advancements in early detection and continuous monitoring to mitigate risks and improve patient outcomes. Early diagnosis is critical as it enables timely intervention, preventing the progression of heart disease and reducing severe complications like heart attacks and strokes [27].

Traditional diagnostic methods such as electrocardiograms (ECGs), echocardiography, and stress tests are commonly used to identify heart disease. However, these techniques have limitations regarding accessibility, cost, and the need for specialized equipment and expert interpretation. For example, while ECGs are effective for detecting arrhythmias, they may not always identify other forms of heart disease unless symptoms manifest during the test. Additionally, conventional diagnostic tools provide only a snapshot of a patient's cardiovascular health at a given moment and do not facilitate continuous monitoring, which is crucial for managing chronic heart conditions.

Advancements in machine learning (ML) have shown promising results in improving the accuracy and efficiency of heart disease diagnosis. Models such as support vector machines, decision trees, and neural networks analyze large and diverse datasets to identify patterns that traditional methods might overlook. Techniques like clustering algorithms and anomaly detection further enhance diagnostic capabilities by identifying high-risk groups and detecting early signs of heart disease, enabling proactive medical intervention [28].

Despite these advancements, conventional ML models face several challenges. Many struggle with handling imprecise, nonlinear, and incomplete medical data, which is common in real-world clinical settings. Moreover, ML models often function as 'black boxes,' offering little insight into how decisions are made. This lack of transparency can hinder acceptance among healthcare professionals who require interpretable diagnostic tools. Hybrid models that combine machine learning with deep learning have been developed to address these challenges, demonstrating improved performance and robustness in heart disease prediction. However, these models still require further optimization to achieve reliable and consistent results across different patient populations and clinical environments.

In addition to ML, novel optimization algorithms, such as the Archimedes Optimization Algorithm (AOA), have been introduced to enhance predictive models for heart disease diagnosis. The Heart Disease Detection Model (HD2M), which uses AOA to choose important features, has shown excellent accuracy and precision in detecting heart problems, doing better than older models in many performance measures. This highlights the potential of integrating advanced optimization techniques with ML to improve reliability in heart disease prediction [29].

Neuro-fuzzy systems have emerged as a powerful computational approach that combines the pattern recognition capabilities of neural networks with the reasoning abilities of fuzzy logic. Neural networks excel at learning from data and recognizing complex, nonlinear relationships, but they often lack interpretability, making them difficult to trust in clinical settings. In contrast, fuzzy logic provides a structured way to handle uncertainty and imprecision, mimicking human reasoning using linguistic variables and IF-THEN rules. This interpretability makes fuzzy logic particularly valuable in medical applications where decision transparency is essential.

By integrating neural networks and fuzzy logic, neuro-fuzzy systems create models that are both accurate and interpretable. These systems effectively manage the ambiguity and variability inherent in medical data, which is often noisy and incomplete. In heart disease diagnosis, symptoms and clinical measurements may not always present clear-cut indicators, and neuro-fuzzy models can accommodate this uncertainty, providing reliable diagnostic support even when data is ambiguous.

A key advantage of neuro-fuzzy systems is their adaptability. They can continuously learn from new data while maintaining a transparent decision-making process, which is critical in healthcare, where patient information is constantly evolving. Bio-inspired algorithms, like genetic algorithms and swarm intelligence, improve these systems by fine-tuning neural network settings and fuzzy rules, which helps the models perform better and apply to a wider range of situations. These optimization techniques are particularly useful in dynamic and uncertain environments, making them well-suited for medical applications [30], [31].

Compared to traditional ML models, neuro-fuzzy systems have demonstrated superior performance in healthcare applications. The use of neutrosophic logic, a generalized form of fuzzy logic, has been shown to improve the accuracy and stability of chronic disease prediction models. This approach effectively addresses the inherent imprecision in medical data, providing more realistic and reliable predictions for conditions such as chronic kidney disease. Similarly, neuro-fuzzy systems have been integrated with deep learning techniques in the context of Internet of Medical Things (IoMT)-enabled devices, enhancing diagnostic accuracy and interpretability for complex conditions like Alzheimer’s disease [32].

Despite progress in methods for detecting heart disease, several gaps remain that limit their effectiveness in clinical practice. Traditional diagnostic techniques, while useful, lack continuous monitoring capabilities and often require significant manual interpretation, increasing the likelihood of variability and potential errors. Machine learning models, although promising, struggle with handling the complexity and inconsistency of medical data. Furthermore, the 'black-box' nature of many ML models limits their acceptance among healthcare professionals, who need transparency in decision-making.

Hybrid approaches that integrate multiple ML techniques have shown promise in addressing some of these limitations. For instance, ensemble models that combine different classifiers improve diagnostic accuracy and robustness. The improved grey wolf-based system for diagnosing monkeypox showed how well hybrid models work in choosing and prioritizing features, resulting in better performance. Such hybrid architectures could be beneficial in heart disease detection, where combining multiple algorithms could enhance reliability [33].

Chronic disease prediction models that incorporate various data sources and machine learning methods have also proven effective. For example, the model that finds early brain strokes uses a type of neural network called a multilayer perceptron along with a special kind of network based on convolutional neural networks, and it has shown better accuracy in diagnosis by combining deep learning with traditional machine learning methods. While these models capture complex relationships in medical data, challenges remain in interpretability and real-time monitoring.

Adaptive modeling techniques that integrate real-time data with analytical models have shown potential in improving the accuracy and generalizability of disease prediction. A combined adaptive modeling system that uses neural networks, which learn from complex patterns, has shown better prediction abilities by continuously learning from changing patient data. Such adaptive systems could enhance heart disease monitoring, providing real-time insights and personalized recommendations [34].

Given these insights, there is a clear need for a hybrid, interpreted, and robust system for continuous heart disease monitoring. A model that mixes the best parts of different machine learning methods, optimization techniques, and easy-to-understand decision-making systems could solve the problems with current detection methods. Neuro-fuzzy systems offer a promising solution, as they integrate neural networks with fuzzy logic to provide accurate, interpreted, and real-time heart disease monitoring. This approach can significantly improve early detection and patient outcomes by addressing current limitations in diagnostic accuracy, model interpretability, and continuous monitoring.

The primary objective of this study is to develop a neuro-fuzzy hybrid model for early heart disease detection. This model will leverage neural networks' ability to identify complex patterns while incorporating fuzzy logic to handle uncertain and imprecise medical data. Additionally, genetic algorithms will be utilized for feature selection and optimization, ensuring the most relevant clinical variables are used to improve diagnostic accuracy and efficiency.

Another key objective is to facilitate continuous monitoring and real-time prediction capabilities. Unlike traditional diagnostic methods, which provide only a static assessment, the proposed neuro-fuzzy model will process continuous streams of patient data, enabling timely interventions. This capability is crucial for detecting early signs of deterioration in patients with existing heart conditions, thereby preventing adverse events and improving patient outcomes.

Ensuring interpretability for clinical decision support is also a fundamental goal. One of the major limitations of deep learning and other ML models is their lack of transparency, which can hinder their adoption in healthcare. The neuro-fuzzy system will solve this problem by combining clear fuzzy logic with neural networks, enabling the model to create understandable rules for its predictions. This will increase trust and acceptance among healthcare professionals [35].

Finally, the study will validate the effectiveness of the proposed model through rigorous testing on diverse clinical datasets. The model's performance will be compared with existing diagnostic approaches by benchmarking its accuracy, sensitivity, and specificity against state-of-the-art systems.

1.2. Types of Heart Failure

Heart disease affects different organs and has unique symptoms, leading to several types of heart failure [36]. In the case of a healthy human heart, the blood vessels known as veins transport oxygen-poor blood from the body to the right side of the heart. The pulmonary artery then pumps this blood into the lungs, where it undergoes re-oxygenation. From there, the blood circulates throughout the body, returns to the left side of the heart, and is pumped through the aorta, which is a major artery [37].

Being chronic and deteriorating, heart failure is a condition that persists over time. Heart damage can develop over time as a result of renal illness, diabetes, high blood pressure, and other endocrine disorders, as well as cardiac problems [38]. Initial compensatory mechanisms are developed by the organ; however, as time goes on, the heart muscles sustain greater harm as a result of these attempts to cope with an increasing strain. The walls of the heart's chambers may narrow as a result of compensatory stretching required to pump more forcefully, or they may thicken as the heart's muscle mass increases, thereby adding to the force available [39].

1.2.1. Left Sided Heart Failure

The heart's left side is typically affected by heart failure, which reduces the amount of oxygen-rich blood transported to the rest of the body [40]. The largest chamber of the heart, the left ventricle, is primarily responsible for generating the force required to pump blood throughout the circulatory system [41]. Two conditions can potentially compromise the left ventricle's blood-pumping ability. In one case, the chamber walls thin and dilate, making it increasingly difficult to contract and pump blood. This condition is known as systolic heart failure [42]. The chambers become rigid and contract, which prevents the heart from pumping out enough blood as the walls thicken. Diastolic heart failure is the medical term for it [43]. However, the main causes of this are CAD and high BP. Moreover, the symptoms of this kind of heart failure are

- Intolerance to exercise
- Fatigue
- Cough
- Low BP
- Edoema
- Increase in weight
- Breathing difficulties while sleeping
- Shortness of breath

1.2.2. Right Sided Heart Failure

Right-sided heart failure (HF) prevents the heart from pumping sufficient blood to the lungs, where it becomes oxygenated [44]. Typically, left-sided heart failure can lead to dysfunction on the right side. When one or both of the heart's pumping systems are impaired, deoxygenated blood tends to accumulate throughout the body, causing swelling in the limbs and abdomen [45]. The causes of right-sided heart failure are [46]:

- Pulmonary hypertension
- Syndrome of acute respiratory distress
- Pulmonary embolism
- COPD
- Left sided heart failure

Furthermore, the main symptoms of right sided HF are [47]:

- Increase in weight
- Chest discomfortness
- Breathing difficulty
- Heart palpitation
- Swelling & fluid retention in lower body

1.2.3. Congestive Heart Failure

Although people sometimes use the terms "heart failure" and "congestive heart failure" (CHF) interchangeably, these two disorders are not the same [48]. When the heart weakens, fluid can back up in the lungs, feet, ankles, and legs [49]. Extra fluid "congests" the tissues and can put harmful pressure on the important organs. Edema is the medical term for this troubling fluid accumulation. In addition to obstructing healthy blood flow, CHF can affect the kidneys' capacity to maintain a healthy balance of salt and water in the body [50]. Symptoms are [51]:

- Chest pain
- Lack of appetite
- Concentration reduced
- Nausea
- Increase in weight
- Swelling in lower body
- Cough with blood spots
- Wheezing
- Intolerance to exercise
- Irregular or rapid heartbeat
- Weakness
- Shortness in breath while lying down or performing any activity
- Fatigue

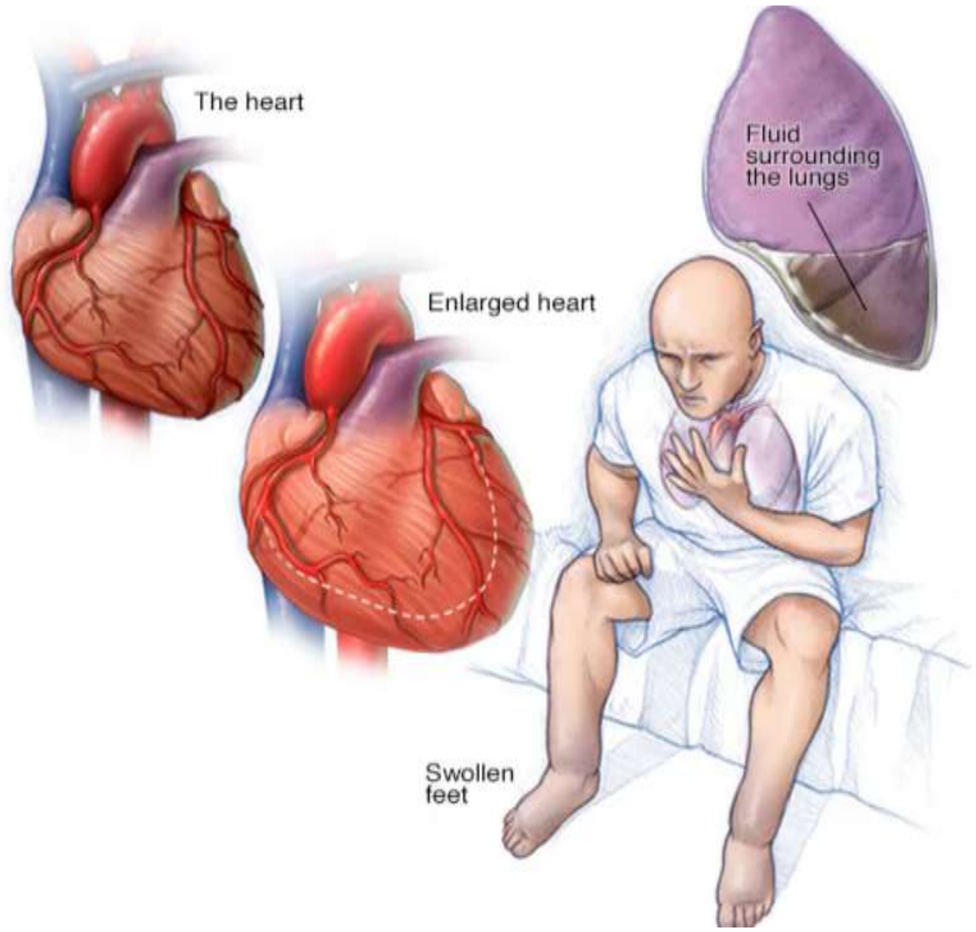

Figure 2: Congestive heart failure [52]

1.3. Risk factors

The patient can control certain risk factors for this deadly illness, but not all of them. Heart disease risk factors that are beyond anyone's control include [53]:

- Race (the individuals who belongs to Mexican American, Native American and African American have more possibility to have this disorder)
- Being postmenopausal
  - Family history
  - Older age
  - Being male

The risk factors for heart disease that are controllable and depend on the patient's lifestyle are [54]:

- Alcohol use
- Poor diet
- Uncontrolled anger, depression and stress
- Uncontrolled diabetes
- Obesity
- Physical activity
- Uncontrolled high blood pressure
- Unhealthy cholesterol
- Smoking

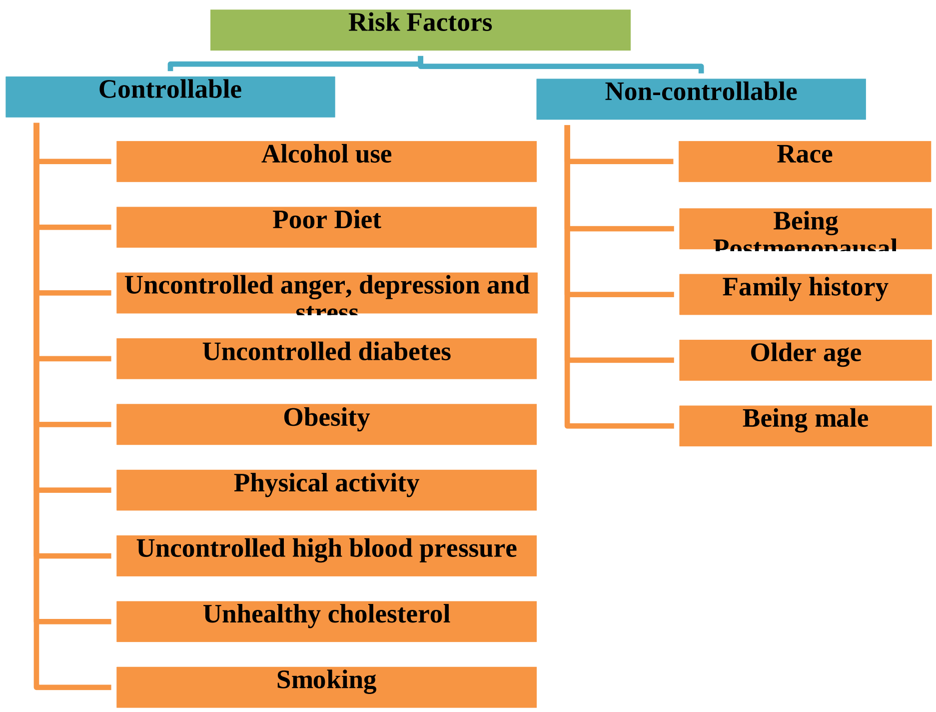

Figure 3: Risk factors

1.4. How to lower the risk

According to research, heart disease can often be prevented by making small alterations to one's lifestyle. These modifications can frequently improve overall physical and mental well-being, in addition to reducing the risk of heart attacks and strokes. The following are some strategies to modify lifestyle choices in order to lower the likelihood of developing heart disease [55]:

- Manage stress
- Maintain a healthy weight
- Rethink before having a drink
- Eat healthy and right
- Stay active
- Control diabetes
- Control high blood pressure
- Improve cholesterol levels
- Quit smoking
-

Figure 4: How to lower the risk?

1.5. Symptoms

1.5.1. Symptoms in blood vessels

Male and female symptoms of heart disease may vary. Men are more prone to experience chest pain, for example. In addition to chest tightness, women are more prone to experience other symptoms such severe exhaustion, nausea, and shortness of breath.

Among the symptoms of heart diseases are [56]:

- If the blood veins in the arms and legs are thin, the patient may experience coldness, weakness, numbness or pain there.
- Back, throat, jaw, neck or upper abdominal region
- Difficulty in breathing
- Chest discomfort
- Chest pressure
- Tightness in chest
- Pain in chest

1.5.2. Signs of heart disease caused by heart valve problem

The tricuspid, pulmonary, mitral and aortic valves are among the heart's four valves. To help the heart pump blood, they open and close. Heart valve injury is a common occurrence. A cardiac valve may narrow, leak, or close incorrectly.

Another name for heart valve disease is valvular heart disease. Heart valve disease symptoms typically include any or all of the following, depending on which valve is malfunctioning [56]:

- Swollen ankles or feet
- Difficulty in breathing
- Irregular heartbeat
- Fatigue
- Fainting

- Pain in chest
- Persistent or dry cough
- Skin rashes
- Fever
- Swelling of belly area or legs
- Unusual spots on skin

1.5.3. Symptoms rise due to heart muscles

The illness in heart muscles' early stage may not show any symptoms at all. Symptoms that emerge as the illness becomes worse include [56]:

- Swollen legs, feet or ankles
- Fluttering, pounding, fast or irregular heartbeat
- Having trouble in breathing while sleeping and waking up
- Feeling out of breath while doing physical activity or just sitting still
- Fatigue
- Dizziness
- Fainting
- Unsteadiness

1.5.4. Signs of heart disease due to defects of congenital heart

Significant congenital heart abnormalities are typically discovered shortly after birth. Children with congenital cardiac defects may exhibit the following signs [56]:

- Breathlessness during feeding in a baby cause low weight gain
- Swelling in the legs, tummy or around the eyes
- Skin or lips that is pale grey or blue

Congenital cardiac abnormalities that are less significant are frequently not discovered until later in infancy or into maturity. Conspicuously non-life-threatening signs of congenital cardiac abnormalities include:

- Feet, ankle and hands swelling

- Easily exhausted by doing any activity
- Easily becoming out of breath while engaging in exercise

1.5.5. Signs due to irregular heartbeat

It's possible for the heartbeat to be excessively fast, too slow, or irregular. Symptoms of heart having irregular heartbeat can include [56]:

- A slow heartbeat
- Breathing difficulty
- Heartbeat that is quick
- Lightheadedness
- Heart palpitations
- Fainting
- Dizziness
- Agony

1.6. Prevention of heart diseases

Because of how quickly and widely heart disease is spreading throughout the world, prevention is crucial [57]. Regardless of where they are from, people should follow certain broad guidelines for primary preventive care [58]. According to local health guidelines, people should eat a healthy diet, get regular check-ups for diseases, and receive proper treatment for illnesses, as these are important for reducing the risk of heart disease, including conditions like high cholesterol, high blood pressure, and diabetes. According to established recommendations, those at high risk may be considered for common drugs like aspirin & statins [59]. Secondary prevention is necessary for people with previous heart disease, and effective medications that have been shown to stop future incidents from happening are also recommended in addition to lifestyle improvements. Figure 5 shows the modification and therapy of risk factors for heart disease.

Over the course of the last 100 years, the global trajectory of CVD has shifted; it began by mostly affecting rich countries and has since expanded to all countries, with lower-income countries accounting for 80% of its early cases [60]. Understanding CVD, recognizing and avoiding risk factors, treating CVD, and introducing changes to one's lifestyle have all advanced. Not all nations experience these advancements equally. To achieve the best results, therapy advancements, risk factor identification, and treatment approaches must be tailored to the specific populations. Recent research indicates that some of the current dietary advice may be out of date and should be examined and, if necessary, altered [61].

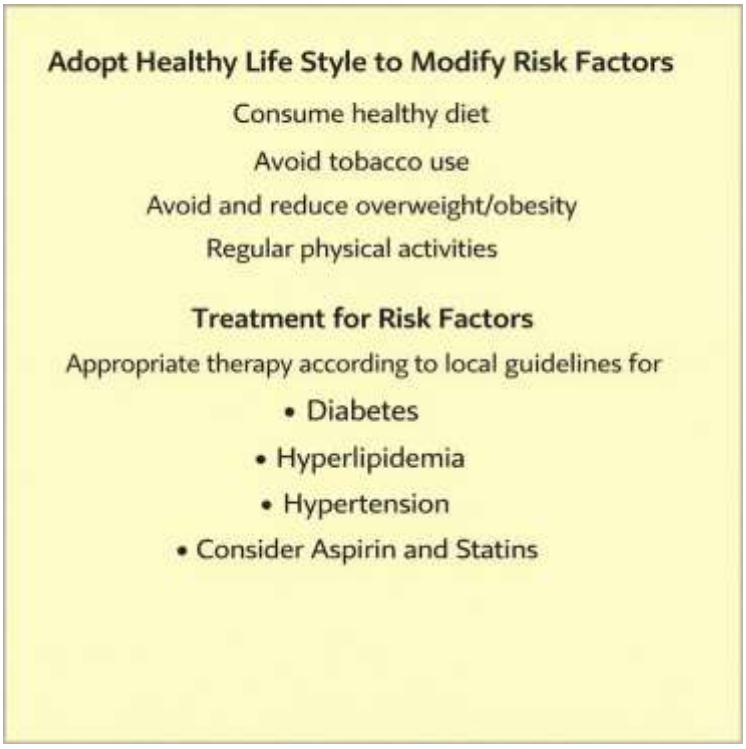

Figure 5: Modification and therapy of risk factors for heart disease [58]

Computer technology has found significant use in this technical era, aiding in patient care, illness treatment, and many medical diagnoses [63]. Although such computer-dependent fields have a high degree of uncertainty and complexity, still intelligent systems like genetic algorithms, artificial neural networks, fuzzy logic, etc., have been developed [63]. Due to the shortcomings of current approaches to diagnosing a disease, it is essential to develop an expert or intelligence system that will assist professional doctors and provide care of high quality to the patient at low expense, regardless of where they are located [64]. Hence, the demand for fuzzy logic increased in the domain of medicine due to its strength in providing correct and exact solutions to challenging real-world problems [65], [66], [67]. Additionally, the growth of the Internet helps expert systems to provide a platform for these models or systems, due to which these systems grab the capability to do work or reasoning similar to a human [68].

Fuzzy logic is the most popular and widely utilized method to identify particular diseases from a patient's laboratory test results in their earliest stages [69]. This technique enables a specialist to diagnose a patient with heart failure efficiently and effectively [70]. Additionally, it will also benefit the suffering individual by saving his or her patience as well as time [71]. Furthermore, this method allows the doctors to prescribe appropriate medication to the patient in order to treat the ailment following a thorough diagnostic [72], [73], [74].

This research work focuses on basically the detection of heart failure in its early stages by using a well-known technique of artificial intelligence named fuzzy logic. The systems developed using this methodology are crucial in medical science, as they help in the accurate diagnosis of numerous disorders. In the modern world, heart-related issues are quite prevalent [75]. The primary cause of increased heart failure risk is the accumulation of excess cholesterol in the blood vessels and arteries [76], [77]. The patient faces several challenges as a result, including depression, trouble sleeping, dyspnea, chest pain, and fatigue [78], [79]. Additionally, these body conditions also increase the risk of stroke and heart attack.

Hong Kong, Japan, and France have the lowest rates of heart failure-related deaths. Meanwhile, the countries having the highest number of deaths due to heart attacks are Africa and India. The percentage of deaths in these two nations due to this disorder is thirty-four percent and twenty-three percent, respectively [80]. Additionally, the estimated deaths due to heart attacks each year are 12M all over the world, as reported by W.H.O. [81]. Due to excessive alcohol, tobacco, and cigarette use, this chronic condition has been a problem in both developed and developing nations for the past forty years [82]. There are several factors, such as smoking, alcohol use, family history, increased blood sugar, high cholesterol levels, hypertension, obesity, age, and gender, which contribute to an increase in the probability of having heart disease [83],

[84], [85]. Moreover, the other risks include disturbed sleep due to a technologically advanced society, changes in routine or diet, stress, being inactive in physical exercises, and the tension of overwork and underemployment owing to industrialization [86], [87]. Furthermore, the major chronic diseases of the heart in patients have been brought in by the huge change in attitudes like narcissism, greed, egoism, and lifestyle change [88].

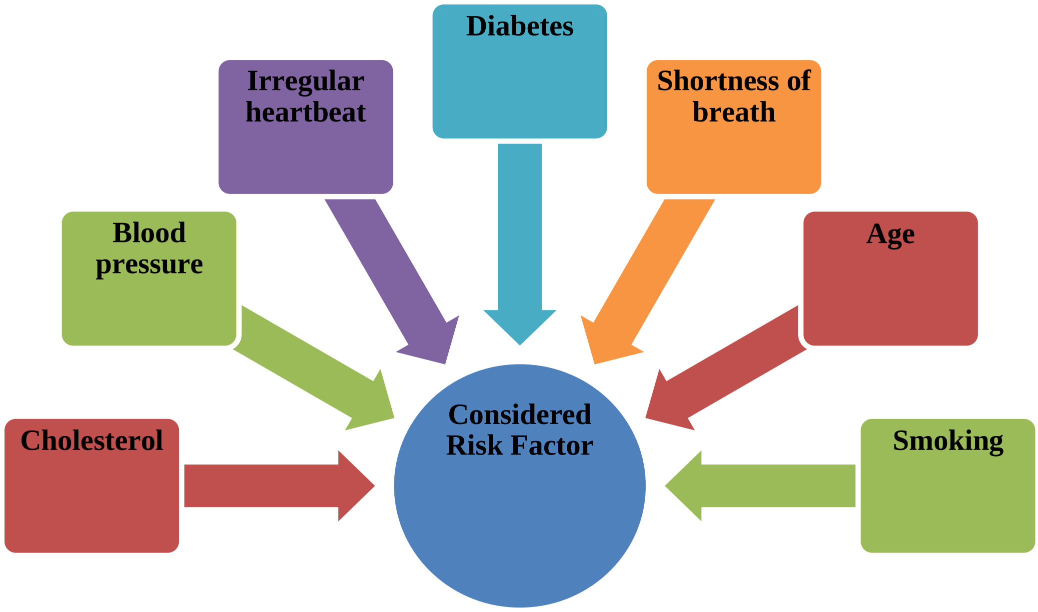

Figure 6: Considered risk factors

Therefore, it is essential to diagnose heart diseases in their early stages so that the chances of heart failure can be decreased [89]. It may be difficult for physicians to diagnose this illness, though, due to the complexity and variability of symptoms [90], [91]. Yet, diagnosing this illness accurately is crucial for effective treatment and management. The ability to identify a heart attack quickly is crucial for both saving the patient's life and preventing further heart damage [92], [93].

Hence, this paper presents the development of a novel intelligence system that allows doctors and patients to monitor heart diseases at the initial phase and can prevent heart failures. We use the fuzzy logic technique to develop the system. Figure 6 illustrates the risk factors that this research work takes into account to develop a diagnosis model. The in-depth detail of each input variable is explained in the further chapter of this report.

1.7. Artificial Intelligence (AI)

The term "artificial intelligence," or "AI," refers to the creation of computer systems or other machines that are capable of carrying out tasks that traditionally require human intelligence [94]. Among them are decision-making, comprehending natural language, pattern recognition, learning from experience, and complicated problem solving, as shown in Figure 7 [95]. AI systems are designed to mimic human cognitive processes in order to analyze data, change course when necessary, and get better over time.

The term "artificial intelligence" (AI) refers to a broad range of tools, methods, and strategies that let machines behave in an "intelligent" way. These behaviours might range from straightforward rule-based judgment to sophisticated machine learning methods that let systems learn from data and classify or anticipate things. As artificial intelligence (AI) has developed throughout time, many subfields have emerged that concentrate on distinct facets of intelligence. These subfields cover various topics, such as robotics, computer vision, natural language processing, and machine learning. The use of AI technology has transformed many industries, from manufacturing and entertainment to healthcare and finance, and it has pushed the limits of what robots are capable of [96].

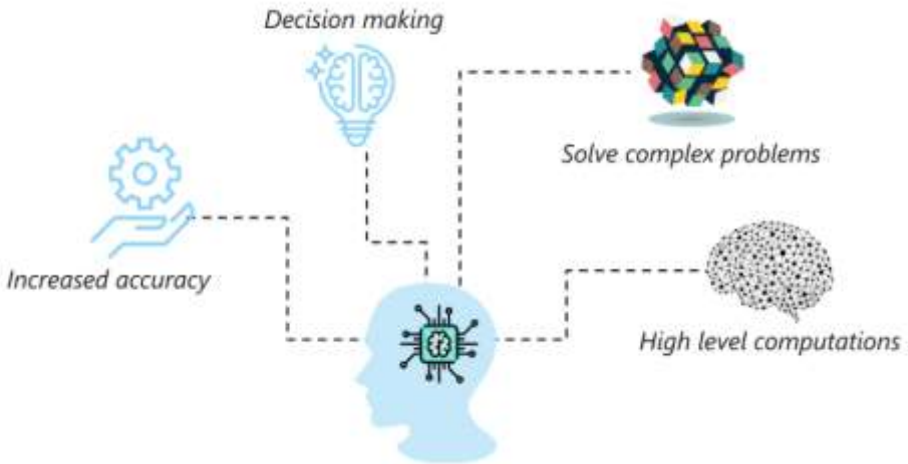

Figure 7: AI in healthcare [95]

The value of AI-powered solutions in the upcoming healthcare technologies is becoming increasingly clear to the industry. The industry believes that AI has the potential to improve any procedure involved in the operation and provision of healthcare. One key factor driving the use of AI applications is the potential cost savings it might provide to the healthcare sector [97]. These cost savings are largely the result of switching from a reactive to a proactive healthcare paradigm that emphasizes health management instead of disease treatment. We anticipate a decrease in hospitalizations, medical visits, and therapy as a result. AI-based technology will significantly assist individuals in maintaining their health through regular evaluations and coaching, ensuring earlier diagnosis, customized therapies, and more effective follow-ups [98]. Figures 8 and 9 display a schematic representation of a model of human intelligence and AI.

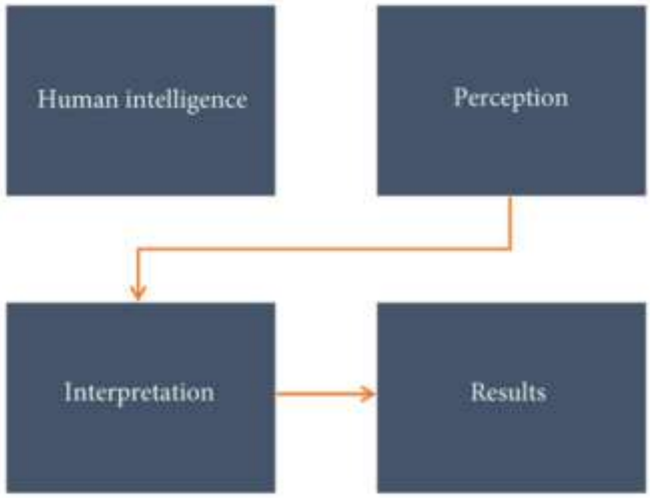

Figure 8: Human Intelligence Model [99]

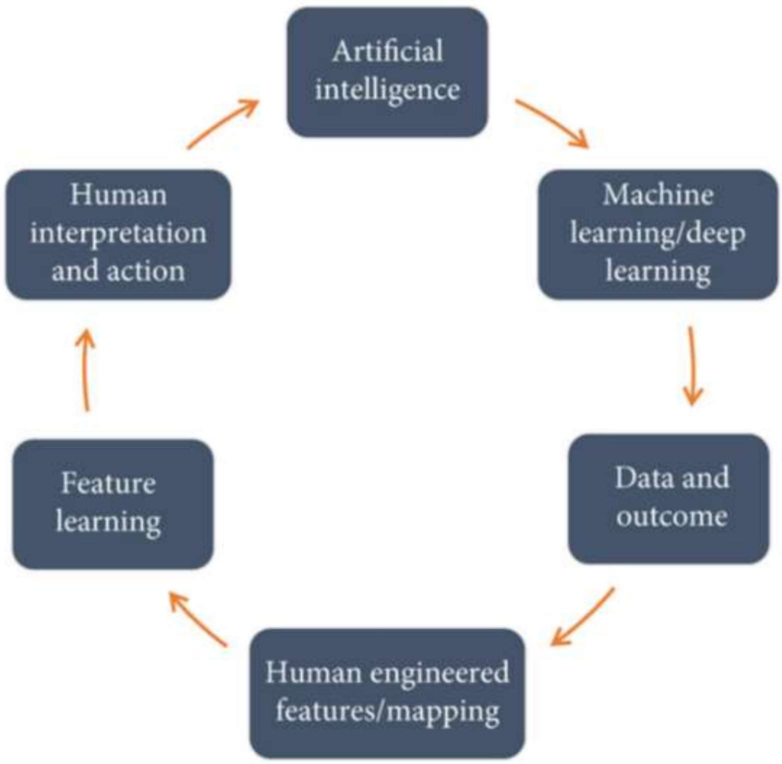

Figure 9: AI model [99]

1.8. Machine Learning (ML)

In general, the exploration of computer algorithms that automate the construction of analytical models is machine learning, one of the most exciting AI technologies. A collection of rules, procedures, or complex "transfer functions" is frequently included in ML models and can be used to find interesting data patterns or to predict behaviour. Figure 10 illustrates the overall structure of a machine learning-based predictive model. In phase 1, the model is trained on historical data, and in phase 2, the results are created for new test data [100].

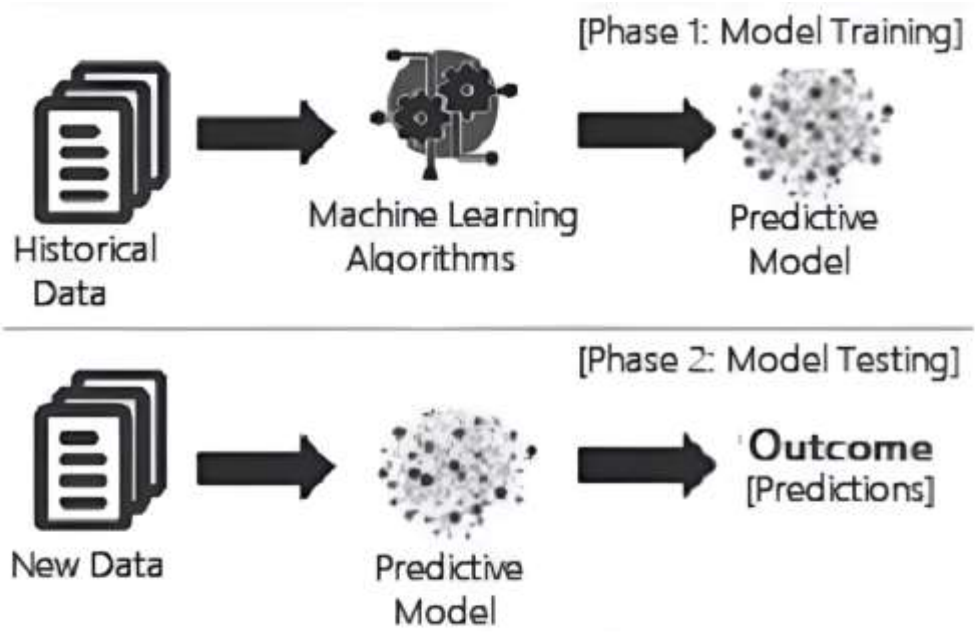

Figure 10: Two phase structure of ML [100]

ML involves making and using algorithms that analyze data and its characteristics to decide what action to take, instead of being directly programmed for specific responses to certain inputs. ML algorithms typically evolve or "learn" when additional data is added. As shown in figure 11, ML algorithms can be broadly classified into four groups [101].

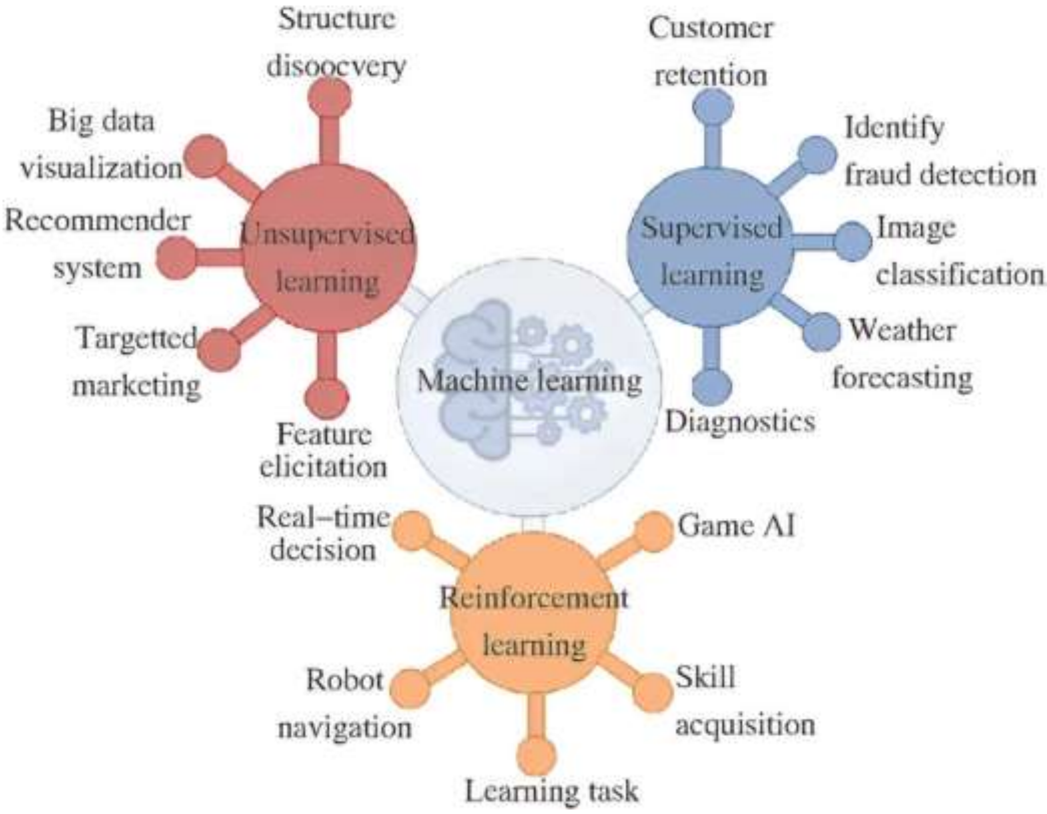

Figure 11: Classification of ML algorithms [101]

1.9. Fuzzy Intelligent System (FIS)

Fuzzy logic is a computing approach that handles the concept of partial truth, where a value can range between completely true and completely false. We have used fuzzy logic to handle the concept of partial truth, where the truth value may vary from absolutely true to completely false. This approach generates the rules as follows: "If "input" is moderate, perform "output1"; if "input" is not moderate, perform "output2. In this case, the distinctions between "moderate" and "not moderate" are fuzzy in nature. Fuzzy logic-based models can thereby recognize, describe, handle, comprehend, and exploit hazy and ambiguous data and information. Its general architecture is displayed in figure 12.

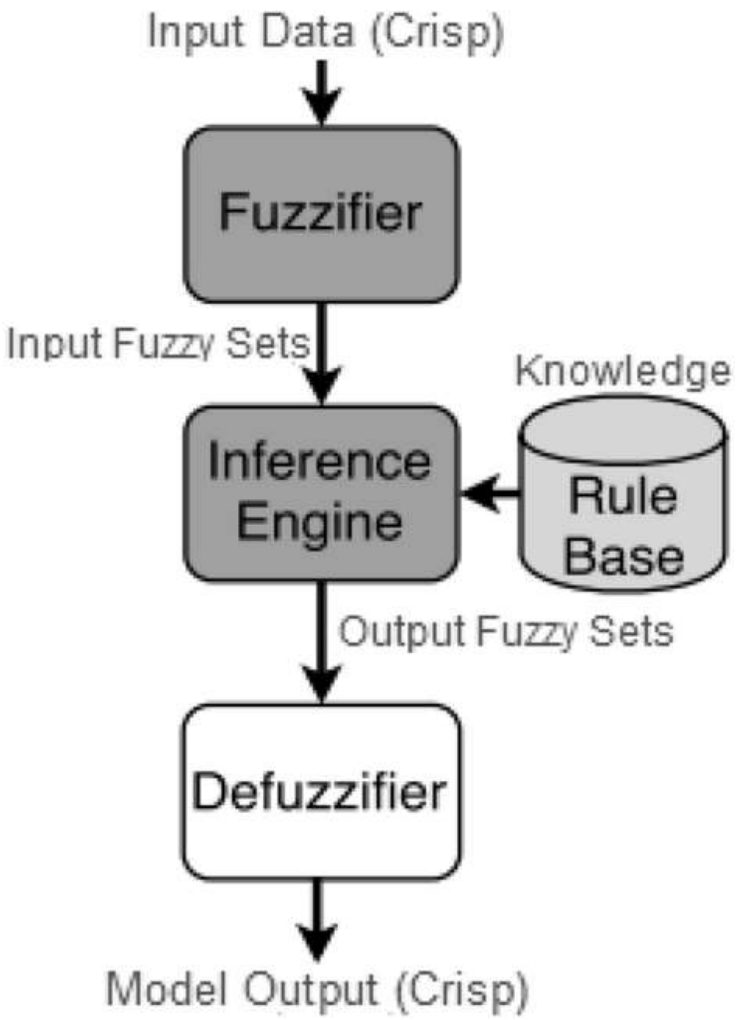

Figure 12: General architecture of fuzzy logic [100]

This approach gathers precise information from the patient by posing relevant questions. Next, fuzzy rules are developed by collecting information from the physician and comparing it with the existing knowledge base [102]. Subsequently, the inference engine, which is a core component of the fuzzy logic system, processes the developed rules. The controller matches the rules stored in the knowledge base, and the most appropriate rule is fired. The system automatically rejects input values that do not correspond to any defined rul. Figure 13 illustrates the general architecture of the expert system.

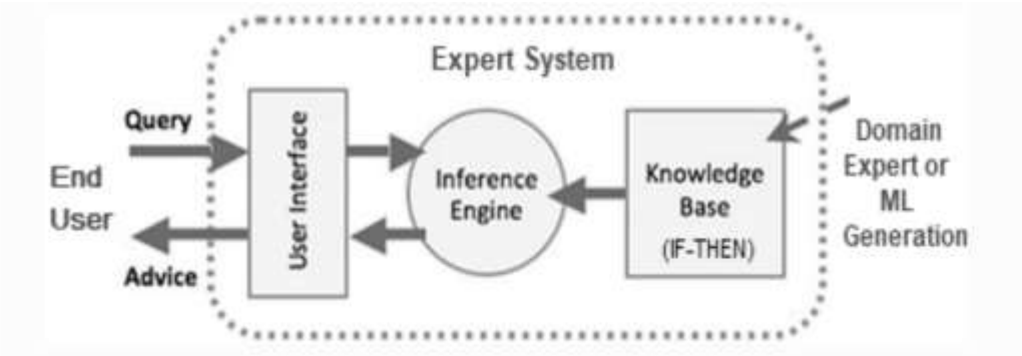

Figure 13: Fuzzy expert system's general architecture [100]

1.10. Artificial Neural Network (ANN)

An artificial neural network (ANN) is a computational model that emulates the functioning of the human brain when performing a specific activity. The connection between two neurons in a neural network is characterized by a specific strength known as the weight or synaptic weight. The threshold function determines the activation state of a neuron. In 1958, Frank Rosenblatt introduced the concept of the perceptron, which refers to the ability of a single-layer network to learn [103]. A key limitation is that a perceptron cannot solve problems in which data points are not linearly separable. Extensive research efforts are still required to address the issue of linear reparability in perceptron networks. Inputs often comprise binary, bipolar, and real-time environmental information.

An artificial neural network (ANN) can contain one or more layers. Its processing units (also known as neurons or nodes) are coupled through a system of programmable weights, allowing signals to pass through the network both concurrently and in parallel. A typical artificial neural network (ANN) can be divided into three layers of neurons: the input layer, which accepts information; the hidden layer, which is responsible for extracting patterns and performing most of the core computations; and the output layer, which generates and presents the final network outputs [104]. The connections between neurons drive neural computing, with each neuron having a single output, a transfer function, and weighted inputs. A neuron's activation is produced by the weighted sum of its inputs, after which the activation signal undergoes a transfer function to generate a single output. The architecture, learning rule, and transfer functions all play a role in determining the overall performance of the neural network [105]. In neural networks, an algorithm is a step-by-step procedure used to achieve specific objectives. Figure 14 depicts the generalized ANN algorithm, including its main steps. Similarly, Figure 15 effectively demonstrates the structural design of multilayered ANNs.

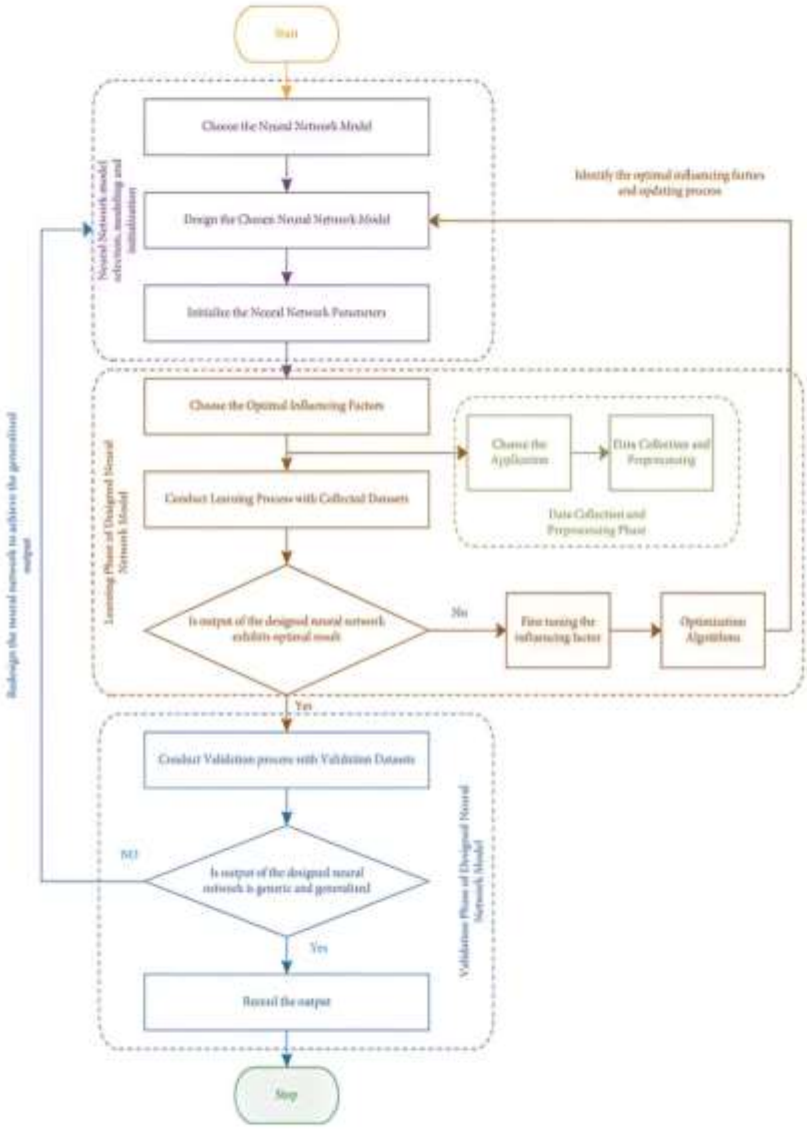

Figure 14: Generalized ANN algorithm [103]

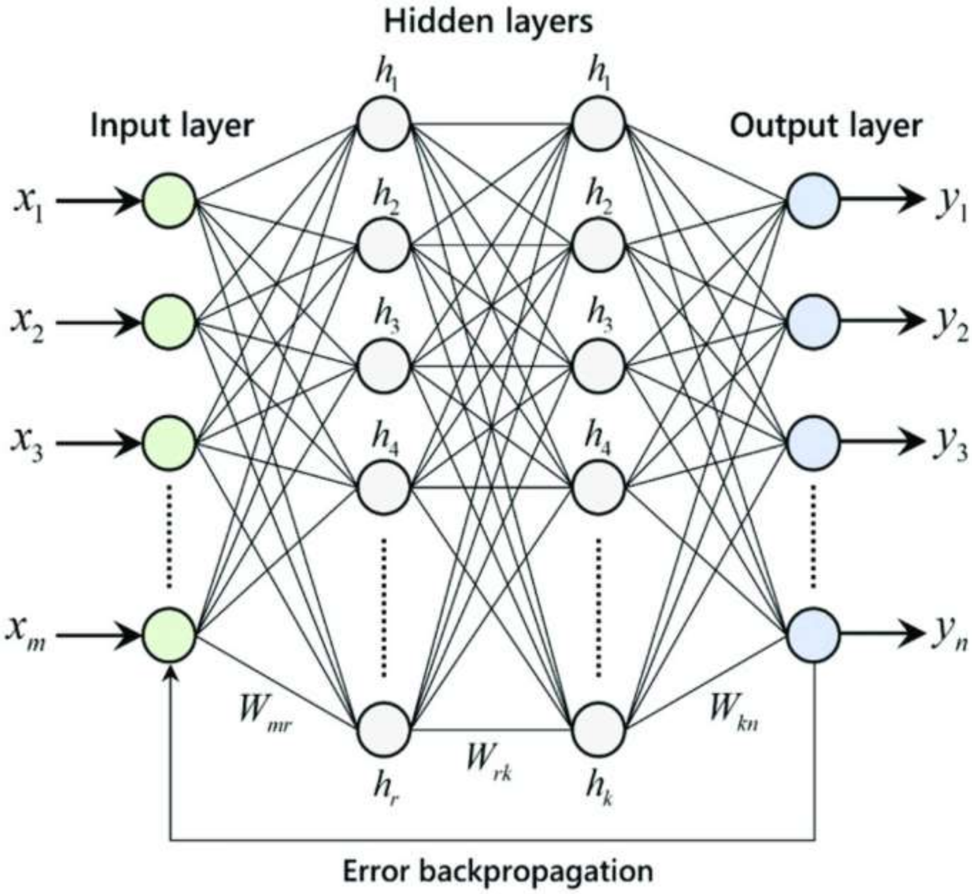

Figure 15: Structural design of multilayered ANN [106]

1.11. Adaptive Neuro Fuzzy Inference System (ANFIS)

To create a clear link between what goes in and what comes out, the ANFIS machine learning method combines fuzzy logic (FL) ideas and ANN rules into a flexible network design. The toolbox component of the ANFIS, when combined with the least squares method, generates an adjustable FIS within the membership attributes. The ANN process creates the ANFIS's FIS framework and trains the model. Figure 16 provides a useful illustration of the ANFIS method. We create an inference system using five layers: the fuzzy layer, product layer, normalized layer, de-fuzzy layer, and the total output layer. Each layer is made up of various nodes, which are symbolized by squares for variables that can be transformed and circles for variables that are unchangeable [107].

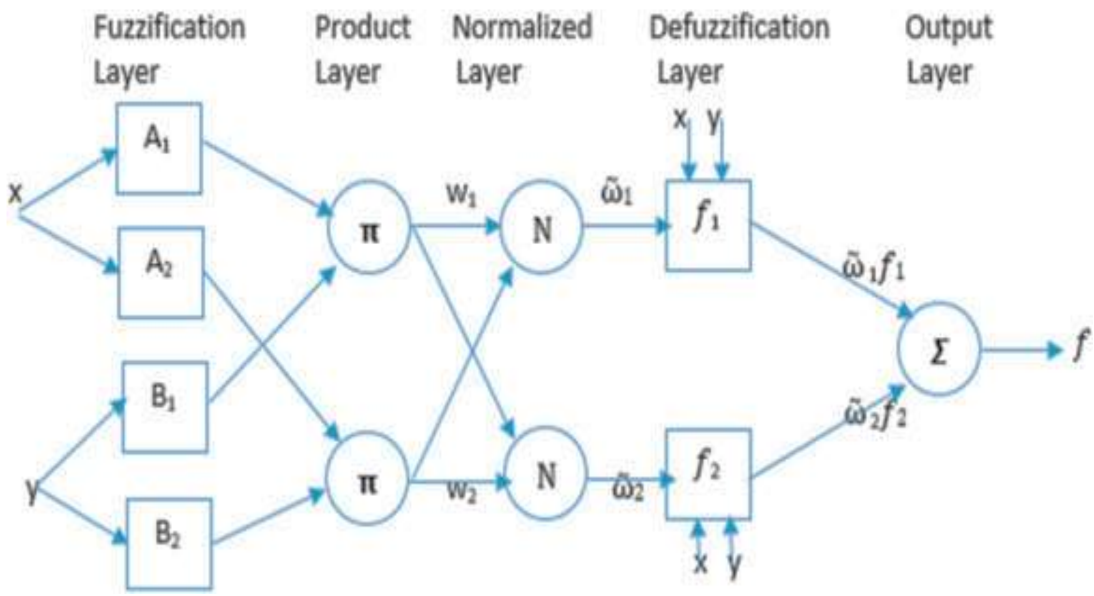

Figure 16: Structure of ANFIS [107]

1.12. Cure and Treatments of Heart Diseases

Heart disease remains a leading cause of morbidity and mortality worldwide, affecting millions of individuals across diverse populations. It encompasses a wide spectrum of conditions, including coronary artery disease (CAD), heart failure, arrhythmias, and valvular heart diseases. The management of these conditions involves a multifaceted approach that incorporates lifestyle modifications, pharmacological interventions, surgical procedures, and emerging technologies. Early detection and continuous monitoring are vital for improving patient outcomes and reducing the global burden of heart disease. This document provides an in-depth exploration of the various treatments and cures available for heart diseases, detailing conventional methods, advanced therapies, and integrative approaches.

1.13. Lifestyle Modifications

Lifestyle modifications form the cornerstone of both the prevention and management of heart diseases. Addressing modifiable risk factors through changes in diet, physical activity, and behavior significantly reduces the risk of developing cardiovascular conditions and improves outcomes in individuals who have already been diagnosed.

Dietary Changes:

A heart-healthy diet is crucial in managing and preventing heart disease. This strategy involves reducing the intake of saturated fats, trans fats, cholesterol, and sodium. High levels of these substances contribute to atherosclerosis, hypertension, and other cardiovascular problems. Increasing the consumption of fruits, vegetables, whole grains, lean proteins, and healthy fats (such as omega-3 fatty acids found in fish, flaxseeds, and walnuts) supports heart health. Specific dietary patterns like the Mediterranean diet and the DASH (Dietary Approaches to Stop Hypertension) diet have been extensively studied and proven to lower the risk of heart disease by promoting balanced nutrition and reducing blood pressure.

Physical Activity:

Regular exercise strengthens the heart muscle, improves circulation, lowers blood pressure, and helps maintain a healthy weight. The American Heart Association recommends at least 150 minutes of moderate-intensity aerobic activity per week, such as brisk walking, cycling, or swimming. Incorporating resistance training and flexibility exercises further enhances cardiovascular health and overall well-being.

Weight Management:

Obesity is a significant risk factor for heart disease, contributing to hypertension, diabetes, and dyslipidaemia. Achieving and maintaining a healthy weight through diet and exercise is essential for reducing cardiovascular risk. Even modest weight loss (5-10% of body weight) can have substantial benefits in lowering blood pressure, improving cholesterol levels, and reducing the risk of type 2 diabetes.

Smoking Cessation:

Smoking damages the lining of the arteries, leading to atherosclerosis, and significantly increases the risk of heart attacks and strokes. Quitting smoking reduces cardiovascular risk almost immediately, with substantial improvements observed within the first year of cessation. Supportive measures such as counselling, nicotine replacement therapy, and prescription medications can enhance the success rate of smoking cessation efforts.

Stress Management:

Chronic stress contributes to heart disease by increasing blood pressure and promoting unhealthy behaviours such as overeating, smoking, and physical inactivity. Techniques like mindfulness meditation, yoga, deep breathing exercises, and cognitive-behavioral therapy (CBT) can effectively reduce stress levels and improve heart health.

1.14. Pharmacological Therapies

Medications play a vital role in the treatment and management of heart diseases. They are used to control symptoms, prevent disease progression, reduce the risk of complications, and improve overall survival. The choice of pharmacological therapy depends on the specific type of heart disease and the individual patient's condition.

Antihypertensives:

Hypertension is a major risk factor for heart disease. Antihypertensive medications help lower blood pressure and reduce the strain on the heart. Common classes of antihypertensives include

ACE Inhibitors : These medications relax blood vessels and reduce blood pressure by inhibiting the angiotensin-converting enzyme.

Angiotensin II Receptor Blockers : These drugs block the action of angiotensin II, a hormone that causes blood vessels to constrict.

Beta-Blockers : Beta-blockers reduce heart rate and blood pressure, decreasing the heart's workload.

Calcium Channel Blockers : These medications relax blood vessels by blocking calcium from entering cells of the heart and blood vessel walls.

Diuretics : Diuretics help reduce blood pressure by removing excess sodium and water from the body.

Antiplatelet Agents and Anticoagulants: These medications prevent blood clots, which can lead to heart attacks and strokes.

Antiplatelet Agents : These drugs inhibit platelet aggregation, reducing the risk of clot formation.

Anticoagulants : These medications interfere with the blood clotting process and are used in conditions like atrial fibrillation to prevent thromboembolic events.

Cholesterol-Lowering Medications: High cholesterol levels contribute to the development of atherosclerosis and heart disease.

- **Statins :** Statins are the most commonly prescribed medications for lowering LDL cholesterol.
- Other lipid-lowering agents include **ezetimibe** (reduces cholesterol absorption in the intestines), **fibrates** (reduce triglyceride levels), and **PCSK9 inhibitors** (e.g., alirocumab, evolocumab), which significantly lower LDL cholesterol.

Nitrates and Anti-Anginal Medications:

- **Nitrates :** Used to relieve chest pain (angina) by dilating the blood vessels and improving blood flow to the heart.
- Other anti-anginal medications include **ranolazine**, which helps improve blood flow and reduce angina symptoms without affecting blood pressure or heart rate.

Heart Failure Medications: Managing heart failure involves multiple medications that improve heart function and reduce symptoms.

- Common drugs include **ACE inhibitors**, **beta-blockers**, **diuretics**, **aldosterone antagonists** (e.g., spironolactone), and **neprilysin inhibitors** (e.g., sacubitril/valsartan).

Antiarrhythmics: Used to control abnormal heart rhythms.

- **Amiodarone**, **flecainide**, and **sotalol** are examples of medications that stabilize the electrical activity of the heart.
- Rate-control drugs such as **beta-blockers** and **calcium channel blockers** help manage conditions like atrial fibrillation.

1.15. Interventional Procedures

When lifestyle changes and medications are insufficient to control heart disease, interventional procedures may be necessary to restore proper heart function or prevent further damage.

Angioplasty and Stenting:

- A minimally invasive procedure where a catheter with a balloon is inserted into a narrowed artery. The balloon is inflated to open the artery, and a stent (a small mesh tube) is placed to keep it open.
- Commonly used to treat coronary artery disease and prevent heart attacks.

Coronary Artery Bypass Grafting (CABG):

- A surgical procedure in which blood vessels from other parts of the body are grafted to bypass blocked coronary arteries, improving blood flow to the heart muscle.
- Typically recommended for patients with severe coronary artery disease or multiple blocked arteries.

Pacemakers and Implantable Cardioverter Defibrillators (ICDs):

- **Pacemakers** regulate slow heart rhythms by sending electrical impulses to prompt the heart to beat at a normal rate.

- **ICDs** are implanted to detect and correct life-threatening arrhythmias by delivering electrical shocks when abnormal rhythms are detected.

Valve Repair or Replacement:

- For patients with valvular heart diseases, procedures like valve repair or replacement (using mechanical or biological valves) are performed to restore normal valve function.
- Minimally invasive techniques such as transcatheter aortic valve replacement (TAVR) have become increasingly popular.

Catheter Ablation:

- A procedure that uses radiofrequency energy to destroy abnormal heart tissue causing arrhythmias, particularly in conditions like atrial fibrillation.

Left Ventricular Assist Devices (LVADs):

- Mechanical devices that help pump blood from the left ventricle to the rest of the body in patients with advanced heart failure.
- Often used as a bridge to heart transplantation or as long-term therapy in patients who are not transplant candidates.

1.16. Advanced Therapies and Emerging Technologies

Recent advancements in medical technology and research have led to the development of innovative treatments and diagnostic tools for heart disease.

Regenerative Medicine and Stem Cell Therapy:

- Research into stem cell therapy aims to regenerate damaged heart tissue and improve heart function in patients with heart failure or after a heart attack.
- Although still in experimental stages, early results are promising, and this approach holds significant potential for future treatments.

Gene Therapy:

- Gene therapy is being explored as a treatment for inherited heart conditions by correcting genetic defects at the molecular level.

- Techniques such as CRISPR-Cas9 gene editing are being investigated for their potential to address genetic mutations associated with cardiomyopathies and other hereditary heart diseases.

Artificial Intelligence and Machine Learning:

- AI-driven diagnostic tools and predictive models are being developed to improve early detection, risk assessment, and personalized treatment of heart disease.

- These technologies analyze large datasets to uncover patterns and make accurate predictions, enhancing clinical decision-making and patient care.

Wearable Devices and Remote Monitoring:

- Devices like smart watches and fitness trackers can monitor heart rate, rhythm, and other vital signs, providing real-time data to healthcare providers.

- Remote monitoring enables continuous assessment of patients' cardiovascular health, allowing for timely interventions and reducing hospital readmissions.

Minimally Invasive and Robotic-Assisted Surgery:

- Advances in surgical techniques, including robotic-assisted procedures, have made heart surgeries less invasive, reducing recovery times and improving outcomes.
- Robotic systems provide greater precision and control during complex cardiac surgeries, enhancing patient safety and surgical success rates.

Cardiac Resynchronization Therapy (CRT):

- CRT involves the use of a specialized pacemaker to coordinate the contractions of the heart's ventricles, improving heart function in patients with heart failure.

- This therapy is particularly beneficial for patients with heart failure and ventricular desynchrony.

Integrative and Complementary Therapies

In addition to conventional treatments, integrative and complementary therapies can play a supportive role in managing heart disease.

Mind-Body Practices:

- Techniques such as meditation, yoga, and tai chi help reduce stress and improve heart health by lowering blood pressure and enhancing overall well-being.

- These practices promote relaxation and emotional well-being, contributing to better cardiovascular outcomes.

Nutritional Supplements:

- Supplements like omega-3 fatty acids, coenzyme Q10, and magnesium may support heart health by reducing inflammation, improving lipid profiles, and enhancing energy production in heart cells.
- However, supplements should be used under medical supervision to avoid potential interactions with prescribed medications.

Acupuncture and Traditional Medicine:

- Some patients find relief from heart-related symptoms through acupuncture and other traditional medicine practices.

- While more research is needed to confirm their efficacy, these approaches may complement conventional treatments in managing certain cardiovascular conditions.

Behavioral Therapy and Counseling:

- Addressing psychological factors such as depression, anxiety, and stress through therapy can improve heart health outcomes.

- Behavioural interventions can help patients adopt healthier lifestyles and adhere to treatment plans, reducing the risk of cardiovascular events.

1.17. Heart Diseases Detection and Techniques

Heart disease remains a significant global health concern, accounting for millions of deaths annually. Early detection of heart diseases is critical for timely intervention, which can significantly improve patient outcomes and reduce the risk of severe complications such as heart attacks, strokes, and sudden cardiac arrest. Various detection techniques, ranging from traditional diagnostic tests to advanced imaging technologies and innovative computational models, play a pivotal role in identifying heart conditions at different stages. This document delves into the diverse methods and technologies employed in the detection of heart diseases, providing a comprehensive overview of their applications, benefits, and limitations.

Traditional Diagnostic Methods for Heart Disease Detection

Traditional diagnostic methods form the foundation of heart disease detection. These techniques are widely used in clinical settings and provide essential information about a patient’s cardiovascular health.

Physical Examination and Detailed Medical History in Cardiovascular Assessment

- The initial step in heart disease detection often involves a thorough physical examination and detailed medical history. Physicians assess risk factors such as family history of heart disease, smoking, hypertension, diabetes, cholesterol levels, and lifestyle habits.
- Physical signs like abnormal heart sounds (murmurs), irregular pulse, swelling in the legs (edema), and elevated blood pressure can indicate underlying heart conditions.

Electrocardiogram (ECG or EKG): Recording the Heart's Electrical Activity

- An ECG records the electrical activity of the heart and helps identify arrhythmias, myocardial infarction (heart attack), and other cardiac abnormalities.
- It is a non-invasive, quick, and widely accessible test that provides a snapshot of the heart's rhythm and electrical function.
- Limitations: While effective for detecting certain conditions, ECGs may not identify heart diseases that do not affect the heart's electrical activity unless symptoms are present during the test.

Chest X-ray Imaging in Heart Disease Diagnosis

- A chest X-ray provides images of the heart, lungs, and blood vessels, helping detect heart enlargement, fluid buildup in the lungs, and other structural abnormalities.
- It is often used to rule out other causes of chest pain or shortness of breath.

Blood Tests: Biomarkers and Indicators of Cardiovascular Health

- Blood tests can detect markers of heart disease, such as elevated levels of cholesterol, triglycerides, and specific proteins like troponin, which indicates heart muscle damage.

- **B-type natriuretic peptide (BNP)** levels are measured to assess heart failure.

Stress Testing: Evaluating Heart Performance Under Stress Conditions

- Stress tests evaluate how the heart performs under physical exertion. The most common type is the **exercise stress test**, where the patient walks on a treadmill while heart rate, blood pressure, and ECG are monitored.
- **Pharmacologic stress tests** are used for patients unable to exercise, involving medications that mimic the effects of exercise on the heart.
- Stress tests help diagnose coronary artery disease and assess the severity of heart conditions.

Advanced Imaging Techniques for Cardiac Diagnosis

Advanced imaging techniques provide detailed visualizations of the heart's structure and function, enabling accurate diagnosis and comprehensive assessment of heart diseases.

Echocardiography: Ultrasound Imaging of the Heart

Echocardiography uses ultrasound waves to create images of the heart. It assesses heart size, shape, and function, and detects conditions such as valvular diseases, cardiomyopathies, and congenital heart defects.

- **Types of echocardiography:**

  - **Transthoracic Echocardiogram (TTE):** A standard non-invasive test where the ultrasound probe is placed on the chest.

- **Transesophageal Echocardiogram (TEE):** Provides clearer images by inserting the probe into the esophagus, closer to the heart.
- **Doppler Echocardiography:** Measures blood flow through the heart and vessels, detecting abnormalities like valve stenosis and regurgitation.
- **Stress Echocardiography:** Combines echocardiography with a stress test to evaluate heart function under stress.

Cardiac Computed Tomography (CT): Cross-Sectional Imaging for Coronary Assessment

- Cardiac CT scans provide detailed cross-sectional images of the heart and blood vessels. They are particularly useful for detecting coronary artery disease and assessing calcium build-up in the arteries (**coronary artery calcium scoring**).
- **CT Coronary Angiography (CTCA)** involves the injection of contrast due to visualizing the coronary arteries, identifying blockages and structural abnormalities.
- **Advantages:** Non-invasive, quick and highly accurate for detecting coronary artery disease.
- **Limitations:** Exposure to radiation and contrast agents, which may not be suitable for all patients

Magnetic Resonance Imaging (MRI): High-Resolution Imaging for Cardiac Function

- Cardiac MRI uses magnetic fields and radio waves to create detailed images of the heart's structure and function.
- It is particularly effective in evaluating heart muscle damage, congenital heart defects, cardiomyopathies, and pericardial diseases.

- **Advantages:** Provides high-resolution images without radiation exposure.
- **Limitations:** Time-consuming, expensive, and not suitable for patients with certain implants (e.g., pacemakers).

Nuclear Cardiology: Radioactive Tracer Techniques for Heart Disease Detection

- Nuclear cardiology techniques, such as **Myocardial Perfusion Imaging (MPI)**, involve the injection of radioactive tracers to assess blood flow to the heart muscle.
- **Positron Emission Tomography (PET)** scans provide detailed information about myocardial viability and perfusion.
- These techniques help diagnose coronary artery disease, evaluate the severity of heart conditions, and guide treatment decisions.

Coronary Angiography: Invasive Imaging for Detailed Coronary Assessment

- Coronary angiography is an invasive procedure that involves the insertion of a catheter into the coronary arteries, followed by the injection of contrast dye to visualize blockages.
- It is considered the gold standard for diagnosing coronary artery disease and guiding interventions like angioplasty and stenting.
- **Risks:** Although generally safe, it carries risks such as bleeding, infection, and allergic reactions to contrast dye.

Electrophysiological Studies and Continuous Cardiac Monitoring

Electrophysiological studies and continuous monitoring techniques are essential for detecting arrhythmias and other electrical abnormalities of the heart.

Holter Monitoring: Continuous ECG Recording Over 24-48 Hours

- A Holter monitor is a portable device worn by the patient for 24-48 hours to continuously record the heart's electrical activity.
- It helps detect intermittent arrhythmias that may not appear during a standard ECG.

Event Monitors: Long-Term Cardiac Monitoring for Intermittent Symptoms

- Event monitors are similar to Holter monitors but are worn for longer periods (weeks to months). They record heart activity when the patient experiences symptoms and activates the device.

Implantable Loop Recorders: Subcutaneous Devices for Extended Rhythm Monitoring

- These small devices are implanted under the skin to provide long-term monitoring of heart rhythms, particularly useful for detecting unexplained fainting or infrequent arrhythmias.

Electrophysiology (EP) Study: Invasive Mapping of Heart's Electrical Activity

- An EP study involves the insertion of catheters with electrodes into the heart to map its electrical activity and identify the source of arrhythmias.
- It helps guide the treatment of arrhythmias, including catheter ablation.

Computational and AI-Based Detection Techniques in Cardiology

Advancements in computational technologies and artificial intelligence (AI) have revolutionized heart disease detection, offering new tools for early diagnosis and personalized treatment.

Machine Learning and Predictive Analytics for Heart Disease Risk Assessment

- Machine learning models analyze large datasets to identify patterns and predict the risk of heart disease.

- Algorithms like **support vector machines (SVM)**, **decision trees**, and **neural networks** have shown high accuracy in classifying cardiac disorders.
- **Applications:** Risk stratification, early detection of coronary artery disease, and prediction of adverse cardiac events.

Deep Learning and Neural Networks for Automated Cardiac Imaging Analysis

- Deep learning techniques, such as **convolutional neural networks (CNNs)**, are used for image analysis in cardiac imaging.
- These models can automatically detect features in echocardiograms, CT scans, and MRIs, improving diagnostic accuracy and efficiency.

Wearable Devices and Remote Monitoring for Continuous Heart Health Assessment

- Wearable devices like smartwatches and fitness trackers can continuously monitor heart rate, rhythm, and other vital signs.
- **Electrocardiogram-enabled wearables** (e.g., Apple Watch) provide real-time ECG recordings, helping detect arrhythmias like atrial fibrillation.
- Remote monitoring enables healthcare providers to track patients' cardiovascular health and intervene promptly when abnormalities are detected.

Telemedicine and Mobile Health Applications for Cardiovascular Care

- Telemedicine platforms facilitate remote consultations and monitoring, making cardiovascular care more accessible.
- Mobile health applications collect and analyze data from wearable devices, providing personalized health insights and recommendations.

Computational Modeling and Simulation for Predictive Cardiology

- Computational models simulate the heart's function, providing insights into disease mechanisms and guiding treatment planning.
- These models are used in research and clinical practice to predict the outcomes of interventions and optimize patient care.

Emerging and Experimental Techniques in Heart Disease Detection

Research and technological advancements continue to introduce new methods for heart disease detection, enhancing diagnostic capabilities and patient outcomes.

Genetic Testing and Biomarkers for Personalized Cardiac Risk Assessment

- Genetic testing identifies inherited mutations associated with heart diseases like hypertrophic cardiomyopathy and familial hypercholesterolemia.
- Emerging biomarkers, such as **high-sensitivity C-reactive protein (hs-CRP)** and **galectin-3**, provide additional information about inflammation and heart failure risk.

Optical Coherence Tomography (OCT) for Coronary Plaque Characterization

- OCT uses light waves to create high-resolution images of the coronary arteries, helping detect plaque characteristics and guide interventions.

3D Printing and Virtual Reality in Cardiac Diagnostics and Surgical Planning

- 3D printing creates accurate models of the heart for pre-surgical planning and education.
- Virtual reality (VR) and augmented reality (AR) technologies provide immersive visualizations of cardiac anatomy and function, enhancing diagnostic and educational experiences.

Nanotechnology in Cardiac Diagnostics: Enhanced Sensitivity and Specificity

- Nanotechnology-based sensors and contrast agents are being developed to improve the sensitivity and specificity of heart disease detection.

Photonics and Laser-Based Techniques for Non-Invasive Cardiovascular Imaging

- Laser-based imaging techniques, such as **photoacoustic imaging**, provide detailed insights into tissue composition and blood flow, aiding in the early detection of atherosclerosis and other cardiovascular conditions.

1.18 Thesis Organization

This thesis is organized into nine chapters to systematically present the research. **Chapter 2** begins with a comprehensive literature review, presenting both a statistical and an in-depth analysis of existing research on heart disease detection using machine learning, fuzzy logic, and hybrid systems. Following this, **Chapter 3** formulates the specific research problem and outlines the primary objectives that guide the study. **Chapter 4** details the crucial initial stages of data collection and pre-processing, describing the methodologies used to prepare the dataset for model development. The subsequent chapters focus on the implementation of the proposed models: **Chapter 5** explains the development of a fuzzy expert system, while **Chapter 6** details the creation of a more advanced intelligent hybrid inference system using a neuro-fuzzy approach. **Chapter 7** presents a thorough discussion of the results, evaluating the performance of both models using key metrics such as accuracy, precision, sensitivity, and specificity. A comparative analysis is conducted in **Chapter 8**, which benchmarks the two developed models against each other and against existing state-of-the-art systems to validate their effectiveness. Finally, **Chapter 9** concludes the thesis by summarizing the key findings, discussing the study's limitations, and proposing directions for future research in the field.

CHAPTER 2: LITERATURE REVIEW

This section presents a literature review that emphasizes the advantages of machine learning methods in detecting heart failure. Therefore, this section provides an overview of various medical diagnostic systems that have been provided by other researchers, applying machine learning techniques for the diagnosis of heart failure.

2.1. Statistical Review

Researchers have conducted a study to highlight the benefits of machine learning. Therefore, the primary objective of the study is to statistically examine the many research papers published by different authors on the creation of inference systems utilizing machine learning. The distinctiveness of this paper is demonstrated in Table I, where a comprehensive comparison between this study and other analyses or review publications is effectively presented.

Table 1: Comparison of this research with other research projects

Author(s) & Reference Number	Publication Year	Disease	Primary Data Used	Secondary Data Used	Hybrid Model	Rule-Based Approach	AI Approaches	Comprehensive Analysis
Jha et al. [146]	2022	Heart Attack	✓✓✓	✗✗✗	✓✓✓ Neural-Fuzzy Hybrid	✓✓	✓✓✓	✓✓
Ali et al. [157]	2024	Heart Disease	✗✗✗	✓✓✓	✓✓ Fuzzy Logic-Based Approach	✓✗✓	✗✗✓	✓✓✓
Kokila & Praveena [32]	2024	Heart Disease	✓✓	✗✗✗	✓✓✓ Genetic Algorithm + Fuzzy	✗✓✓	✓✓✓	✓✓✓

Taylan et al. [134]	2023	Cardiovascular Diseases	✗✗✗	✓✓✓	✓✗✓ Neuro-Fuzzy + Statistical	✓✓✓	✗✗✗	✗✓✓
Kasbe & Pippal [78]	2017	Heart Disease	✓✓✓	✗✗✗	✓✓ Fuzzy Logic Diagnosis	✗✓✓	✗✗✓	✗✗✗
Our Proposed Work	2025 (Expected)	Heart Disease Detection	✓✓✓	✓✓✓	✓✓✓ Hybrid Inference System	✓✓✓	✓✓✓	✓✓✓

2.1.1. Discussion of Comparative Framework

Table 1 presents a high-level comparison of this thesis with other key research papers in the field of heart disease prediction. The table uses a qualitative scoring system to evaluate each study against several important criteria, including the type of data used, the modeling approach, and the depth of the analysis. This framework helps to quickly visualize the contributions and limitations of existing work and highlights the position of our proposed system.

The symbols used in the table should be interpreted as follows:

- **✓✓✓ (High Emphasis):** This score indicates that the attribute is a central and strongly implemented component of the research.
- **✓✓ (Medium Emphasis):** This score is used when an attribute is present and addressed but is not the primary focus of the study.
- **Mixed Symbols (e.g., ✓✗✓, ✗✗✓):** These symbols denote a partial or limited implementation. For example, a study might use a rule-based approach, but it may not be a core part of its methodology, or a hybrid model may be mentioned but not fully developed.

- ✗✗✗ **(Not Addressed):** This score signifies that the attribute is completely absent from the research paper.

As illustrated in the table, many recent studies leverage hybrid models and advanced AI approaches. However, there is significant variation in their reliance on primary versus secondary data and the comprehensiveness of their analysis. For example, the studies by Jha et al. [146] and Kasbe & Pippal [78] are notable for their use of primary patient data, while others such as Taylan et al. [134] and Ali et al. [157] focus on secondary datasets . Our proposed work aims to provide a more holistic solution by achieving a high score across all criteria. It integrates a hybrid inference system that uses both primary and secondary data, employs a rule-based approach to ensure interpretability, and delivers a comprehensive analysis, thus addressing the gaps identified in existing literature.

2.1.2. Considered Journal Comparison

Combining fuzzy logic with artificial intelligence, Jha et al. (2022) [146] proposed a Neural-Fuzzy Hybrid Model for heart attack prediction, hence raising diagnostic accuracy. Focusing on ECG signals and patient history as input, the study generated an output risk score using primary patient data. Part of the promise of enhanced model prediction interpretability was a rule-based approach applied. The study did, however, identify a research deficit in real-time validation, which would undermine its relevance in clinical settings. The excellent prediction accuracy of the data exposed the potential efficiency of fuzzy logic in cardiac illness identification. The findings considerably enabled integrated hybrid artificial intelligence approaches for early identification and risk assessment of heart attacks.

Ali et al. (2024) [157] presented a fuzzy-logic-based method to improve heart disease diagnostics. This work improved categorization accuracy by means of secondary patient data gathered from many healthcare sources. The model depended on rule-based techniques to improve interpretability and fuzzy logic for handling uncertainty. One important result was that, in complicated cardiovascular diseases, fuzzy inference systems outperformed conventional machine learning methods. One noted restriction, though, was the absence of a thorough real-time dataset. The work greatly helped to integrate artificial intelligence into cardiovascular risk prediction, therefore improving the decision-support tools available to medical practitioners.

Kokila & Praveena (2024) [32] suggested a hybrid AI model for heart disease prediction by combining genetic algorithms with fuzzy logic. To improve predictive accuracy, the model made use of primary patient data together with clinical criteria and past patient knowledge. A partially rule-based framework enhanced transparency in diagnosis decision-making. The hybrid method revealed difficulties in computing efficiency due to the complexity of genetic optimization methods even if it displayed outstanding accuracy in model evaluation. Emphasizing the requirement of more real-time clinical validation, the studies made a major contribution to the creation of AI-driven diagnostic systems. Taylan et al. (2023) [134] wanted to better predict early heart disease by combining different statistical methods with a neuro-fuzzy hybrid model. Using past health records and ECG signal analysis, the study aimed to estimate heart disease risk using secondary patient data. The decision-making process was improved, and the model's explainability was raised by means of a rule-based fuzzy system. The study admitted that real-time adaptation in clinical environments remained a difficulty even if the model enhanced forecast dependability. The results underlined the need for hybrid artificial intelligence approaches in the diagnosis of cardiovascular diseases by providing possible options for early identification and automated risk analysis. Kasbe & Pippal (2017) [78] put forth a fuzzy logic-based diagnostic tool to improve heart disease classification. Using clinical symptoms and medical history to hone predictions, the study concentrated on main patient data. Model interpretability and accuracy were raised by the use of a hybrid rule-based inference method. Despite the study's observation that fuzzy systems alone may not be flexible enough to handle varied datasets, the integration of these systems with deep learning models presents a promising research topic, even if they yield good classification results. Especially in cardiovascular diagnostics, the study significantly helped to advance AI-driven decision support systems.

2.1.3. Advantages of using ML techniques for the detection of heart disease

In the field of medicine, patient records are stored as electronic health records (EHR). With the advancement of healthcare systems, these records are now accessible on websites, thanks to the availability of big data. Furthermore, we utilize this data to construct a diagnostic model for various illnesses, including heart diseases. We analyze this large dataset from various perspectives using machine learning techniques to uncover valuable insights. Furthermore, the system's effectiveness depends on the information or data it receives.

Therefore, there is a possibility of error while imparting knowledge to the system, as the system's inputs rely on human intervention. However, the use of Internet of Things (IoT) devices can reduce the likelihood of errors. These intelligent gadgets will autonomously retrieve the inputs from the patient without any human intervention and thereafter transmit the collected data to the machine learning classifier for the prediction of the disease.

2.1.4. Research Methodology

A methodology is a systematic approach used by authors and researchers to conduct an examination. It involves a thorough analysis of existing literature and the proposal of improved solutions for a specific problem, leading to a well-founded result and choice. The evidence-based research technique is a highly important methodology in researching in the medical field, as it provides practitioners and experts with several treatment options and decision-making systems that have the highest level of accuracy. Hence, this research endeavor involves doing a methodical and statistical examination of the diverse data gathered from the literature review, shedding light on the application of machine learning techniques for the identification of heart disease.

2.1.4.1. Literature Search

A literature search is a systematic process of identifying, reviewing, and analyzing existing scholarly work related to a specific research topic. It involves collecting relevant information from trusted sources such as journals, conference papers, books, and databases to understand prior findings and current developments in the field. This process helps researchers recognize research gaps, refine the problem statement, and build a strong theoretical foundation for the study. In this work, the literature search supports the understanding of existing approaches and highlights the role of machine learning techniques in heart disease identification.

2.1.4.2. Choosing Eligible Papers and Studies

Prior to commencing any research work, it is essential to compile the literature that is most appropriate and pertinent to the conducted study. Therefore, we established eligibility criteria and initially assessed all the documents based on these parameters. This criterion encompasses the publication year, relevance to heart disease, and the creation of a machine learning model. Moreover, we initially assessed a research paper based on its abstract and title before undergoing the eligibility test. Only papers that fully satisfied all the conditions were chosen for the study.

2.1.5. Result & findings

2.1.5.1. Distribution of selected papers on the basis of their year of publication

We selected 156 research publications overall, released between 2015 and 2025, for this analysis. We selected these publications based on their potential to apply machine learning in supporting the diagnosis of heart disease. The year of publication defines the distribution of the chosen papers, as Figure 17 shows. 2022 shows a clear trend whereby studies using machine learning approaches to create models supporting healthcare professionals in diagnosing cardiovascular diseases showed a significant increase (19.23%). Growing awareness of the advantages machine learning provides such as enhancing diagnostic accuracy, streamlining healthcare workflows, and supporting clinical decision-making procedures helps one to understand this rise. Furthermore, driving the creation of more strong and dependable diagnostic tools for cardiovascular disorders is the increase in research effort in 2021 and 2022, reflecting developments in data collection, computational resources, and the refining of ML approaches.

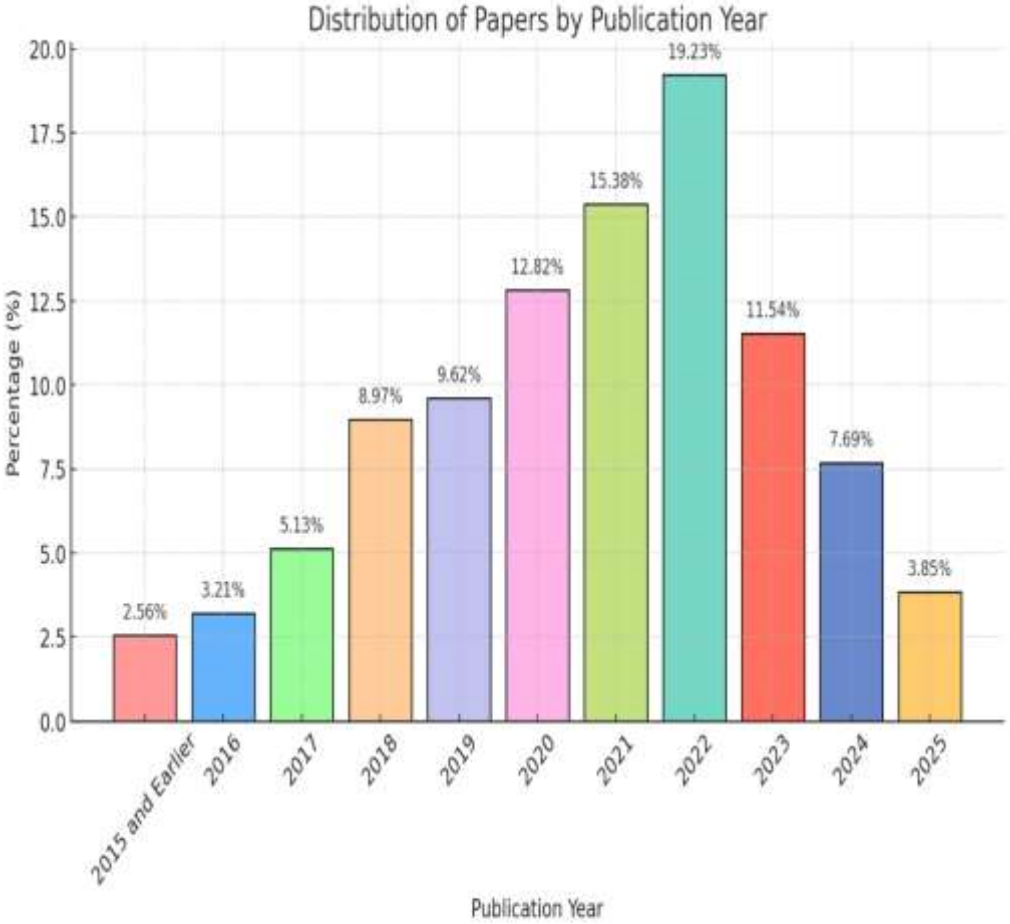

Figure 17: Distribution of selected papers on the basis of their year of publication

2.1.5.2. Distribution of selected papers on the basis of their database providers

Table 2 shows the different databases that are explored in order to find the most relevant and suitable papers for this study. The database provider who has maximum participation in the study is IEEE, and in contrast, Elsevier has the least contribution

Table 2: Distribution of selected papers on the basis of their database providers

Database Provider	Number of Papers	Percentage (%)
Scopus	55	35.26%
IEEE Xplore	28	17.95%

PubMed	18	11.54%
Springer	15	9.62%
Elsevier	12	7.69%
Hindawi	10	6.41%
ResearchGate	8	5.13%
MDPI	6	3.85%
arXiv	4	2.56%
Others (Web, Reports, etc.)	10	6.41%
Total	156	100%

2.1.5.3. Distribution of selected papers on the basis of ML techniques

The primary goal of this review is to examine various models constructed using machine learning approaches. To achieve this objective, Table 3 categorizes the selected papers based on the ML techniques used. The most commonly employed machine learning techniques are ANN and random forests. Based on the analysis of this table, it is evident that in recent years, machine learning (ML) approaches have consistently outperformed models produced using other technologies.

Table 3: Distribution of selected papers on the basis of ML techniques

ML Approaches	Frequency	Percentage (%)	Reference Numbers
Artificial Neural Networks (ANN)	22	14.10%	1, 22, 31, 32, 35, 51, 72, 100, 101, 103, 105, 106, 113,

			115, 118, 122, 125, 126, 129, 134, 138, 144
Fuzzy Logic (FL)	18	11.54%	6, 7, 32, 33, 34, 36, 66, 68, 70, 78, 79, 100, 132, 134, 135, 142, 143, 147
Support Vector Machines (SVM)	15	9.62%	6, 14, 16, 20, 24, 44, 60, 90, 92, 95, 112, 121, 125, 140, 143
Decision Trees (DT)	14	8.97%	10, 20, 28, 45, 58, 64, 85, 88, 99, 116, 118, 121, 124, 139
Random Forest (RF)	13	8.33%	12, 20, 27, 42, 48, 61, 70, 75, 93, 108, 122, 133, 136
K-Nearest Neighbors (KNN)	10	6.41%	20, 44, 53, 56, 74, 80, 91, 107, 114, 140
Deep Learning (DL)	15	9.62%	22, 24, 35, 41, 55, 60, 87, 89, 96, 98, 104, 122, 127, 130, 148

Hybrid Models (ML + FL, DL + RF, etc.)	20	12.82%	8, 17, 26, 29, 32, 37, 39, 47, 58, 63, 71, 81, 92, 97, 109, 123, 128, 132, 137, 150
Adaptive Neuro-Fuzzy Inference System (ANFIS)	10	6.41%	32, 34, 36, 38, 105, 106, 107, 132, 145, 149
Logistic Regression (LR)	6	3.85%	11, 18, 40, 50, 65, 119
Bayesian Networks (BN)	5	3.21%	13, 19, 21, 46, 120
Reinforcement Learning (RL)	3	1.92%	25, 30, 140
Other ML Approaches (XGBoost, Ensemble, LSTM, CNN, etc.)	15	9.62%	9, 23, 33, 49, 59, 67, 76, 82, 86, 94, 102, 110, 111, 141, 146

2.1.6. Discussion

This comprehensive study has conducted an investigation into the numerous advantages and the importance of utilizing machine learning. The study considers and reviews research papers published between 2015 and early 2025 that focus on developing diagnostic models for heart disease using machine learning. The publications are carefully reviewed and assessed against specific qualifying criteria before being selected for this study. Furthermore, the chosen articles are categorized based on the machine learning methodologies used, the database sources, and the publication year. Decision trees and random forests are two of the most commonly employed machine learning algorithms. This analysis indicates that machine learning (ML) models developed in recent times perform better than models using alternative methodologies. Therefore, this review will help the reader analyze the importance of machine learning in creating diagnostic systems for detecting heart disease. Additionally, the frequency of the ML approaches is demonstrated in Figure 2.

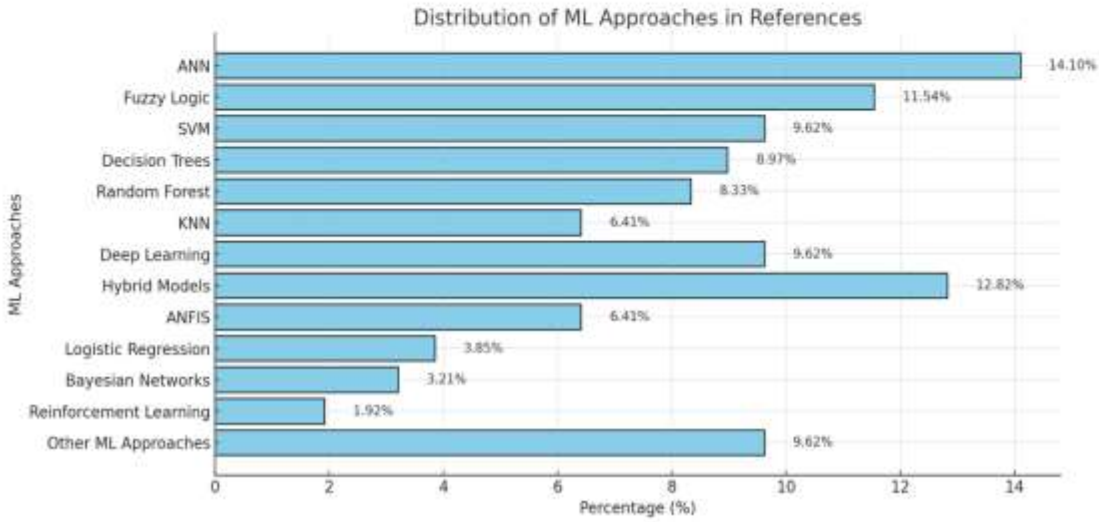

Figure 18: Frequency of the ML approaches

2.2. Comprehensive Review

- Chang et al. (2022) [113] showcased the application of AI technology in predicting the likelihood of an individual developing cardiac disease. The project primarily focuses on the creation of an AI- and ML-based system for accurately identifying cardiac diseases. The authors designed an application using the Python programming language, chosen for its reliability in developing various health monitoring applications. They utilized the Random Forest classifier algorithm to improve the accuracy of heart condition detection. The application achieves an accuracy rate that is approximately 83 percent, which is higher than the accuracy rate obtained from the training data. The performance of the Random Forest classification method undergoes rigorous testing and analysis of the results. Currently, this method enhances diagnostic precision, while the expenses associated with developing the application remain minimal.

- Chicco and Jurman (2020) [23] analyzed data from 299 individuals with heart failure that was collected in 2015. The researchers employed various machine learning methods, like gradient boosting, naive Bayes, kNN, SVM, artificial neural networks, decision trees, random forests, and linear regression, to understand which factors are most important for predicting patient survival in heart failure. Along with standard biostatistical tests, they also did a special analysis to rank features and looked at the results from the machine learning methods. The random forest classifier showed a biostatistical test. This research additionally performs a distinct feature ranking analysis and evaluates the results generated by the machine learning algorithms. The random forest classifier exhibits the highest accuracy, specifically 74 percent, compared to all other classifiers. Further additionally, using these chosen features on their own can lead to better detection of heart failure. Additionally, using these selected features individually can result in improved identification of heart failure.
- Kumar et al. (2021) [114] assessed the latest advancements in the field of quantum-enhanced machine learning and its significance in the early detection of heart failure. They utilized a dataset containing fourteen variables, for which the number of qubits used in this work is standardized based on the properties of the heart failure (HF) data, employing standard scaling, principal component analysis (PCA), and min–max normalization techniques. Finally, they have implemented the pipelining strategy to enhance the process's efficiency research demonstrates. The study shows that quantum-enhanced machine learning methods, like quantum Gaussian Nave Bayes (QGNB), quantum decision tree (QDT), quantum k closest neighbour (QKNN), and quantum random forest (QRF), work better than regular machine learning methods at identifying HF. The quantum random forest classifier did the best among all the classifiers tested, achieving an

accuracy of 89% in classification. The first classifier outperformed all other classifiers examined in this study, with an accuracy of 89% for classification. Figure 19 illustrates the suggested design of the system. The quantum random forest classifier achieved good results in terms of precision, recall, and F1-score, with percentages of 89, 93, and 88, respectively. In addition, a comparison has been conducted to assess the execution speeds of traditional machine learning approaches and quantum-enhanced machine learning approaches. Consequently, the quantum random forest algorithm demonstrates the fastest execution time, specifically 150ms. This research presents a method for quantitatively assessing the disparities between quantum-enhanced and traditional machine learning algorithms to determine the most effective technique for detecting heart failure. Sends a way for quantitatively assessing the disparities between quantum-enhanced and traditional machine learning algorithms in order to determine the most effective technique for detecting heart failure.

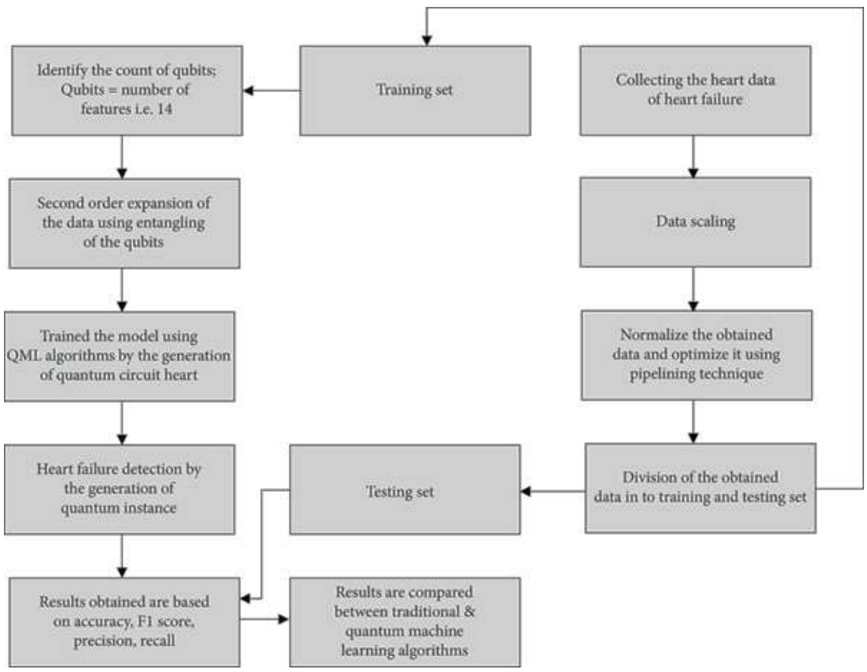

Figure 19: Proposed design [114]

- Umer et al. (2022) [115] employed Internet-of-Things (IoT) and cloud technologies to develop a sophisticated healthcare platform. This platform improves the survival predictions of heart failure patients without the need for manual feature engineering. The strategy employed deep learning models to distinguish between surviving and deceased individuals with heart failure. The intelligent Internet of Things (IoT) framework monitors patients using real-time data and provides heart failure patients with timely, effective, and high-quality healthcare treatments. The approach utilizes Internet of Things (IoT) sensors to collect data and send it to a cloud-based web server for processing. Machine learning algorithms analyze these signals to determine the patients' health. A healthcare professional with the ability to provide immediate aid can get the patient's medical records and treatment results. They accessed the Art Failure Clinical Records repository at UCI to obtain the dataset for this research, which comprises thirteen variables. Empirical results demonstrate that the CNN model outperforms alternative machine learning and deep learning approaches, with an accuracy rate of 92.89 percent.
- Khan (2020) [116] proposes a modified deep convolutional neural network as a component of an Internet of Things (IoT) framework for more accurate assessment of cardiac illness. The patient's paired smart watch and heart monitor measure their blood pressure and electrocardiogram. They employ CNN to classify the data collected by sensors into abnormal and normal states. They test the performance of the constructed system by comparing it with logistic regression and current deep learning neural networks, using the proposed MDCNN as the benchmark. Results demonstrate that the heart disease classifier based on MDCNN surpasses other methods in terms of performance. The proposed methodology shows that the MDCNN achieves a classification accuracy of 98.2 percent for the highest number of records, surpassing traditional classifiers.
- Using machine learning and the Internet of Things (IoT), Ziryawulawo et al. (2022 [112]) investigated methods for evaluating and detecting heart illness. The Internet of Things (IoT) will assist individuals and healthcare providers in the early diagnosis and evaluation of cardiovascular diseases. This paper compares

Internet of Things (IoT) approaches that utilize machine learning (ML) techniques for heart failure prediction and diagnosis. The study was evaluated based on the different performances of the built models. Included in the comparative study are distinct parameter assessments, including classification error, accuracy, F1-score, recall, and precision. The authors of this work concluded from the final results that a model constructed utilizing MSO-ANFIS can effectively detect and continuously monitor heart abnormalities in patients.

- S & U (2022) [124] developed an innovative technique for monitoring cardiac disease with the aim of safeguarding patients. This system integrates the Internet of Things (IoT) with deep learning technologies. This research employs a novel feature selection method to enhance classification accuracy by utilizing a deep learning algorithm. The heart disease monitoring system tracks the severity of the condition based on the data received by Internet of Things (IoT) devices. Furthermore, it classifies patient data according to various heart conditions and their respective levels of seriousness. Moreover, utilizing the provided inputs, it transmits an alarm or message to patients based on the specific type of heart disease. The investigations have demonstrated that the constructed model exhibits a higher level of accuracy in its predictions, with a precision rate of 95.12 percent.
- Kaur (2021) proposed a system [117] that utilizes machine learning (ML) methods and the Internet of Things (IoT) to anticipate heart diseases. This study involves connecting IoT sensors to the patient's body to collect necessary information and create a dataset. Machine learning classification methods to distinguish between normal and pathological conditions based on the provided patient data. Different machine learning classifiers used in this study include Bayes Net, Random Forest, Simple Logistic, Decision Tree, K-Star, Zero R, Naïve Bayes, and J48. They evaluate these classifiers by comparing their respective classification accuracies. The method utilizing the J48 classifier demonstrated the best accuracy, specifically 92.56%. Therefore, this advanced method yields favorable outcomes, facilitates monitoring of the health of people with heart disease, and offers dependable data on illnesses.
- Sarmah (2020) [118] created a patient monitoring system for individuals with heart conditions. This system utilizes an IoT-focused deep learning modified

neural network to assist in the administration and diagnosis of heart disease medicines, as shown in Figure 20. The author in this research employs a three-stage process to effectively accomplish the stated framework. The process consists of three stages: authentication, encryption, and classification. Firstly, the SHA-512 algorithm and the SC cipher authenticate an individual with heart disease at a healthcare center. A surgically inserted wearable Internet of Things sensor transmits real-time sensor data to the cloud. The PDH-AES technique securely encrypts sensor data before transmitting it to the cloud. Next, we decrypt the encrypted data and finalize the classification process by using the DLMNN classifier. The system categorizes the results into two distinct groups: normal and aberrant data. The device provides an assessment of the patient's cardiac health, and if any abnormalities are detected, a notification is delivered to the doctor by text message, enabling prompt treatment of the patient. Based on estimated study findings, the Deep Learning Multilayer Neural Network (DLMNN) outperforms current strategies in the identification of cardiac diseases. In comparison to the current AES, the newly introduced PDH-AES system for safe data transmission achieves a maximum security level of 95.87%. Additionally, it accomplishes this in the quickest possible time for both encryption and decryption processes.

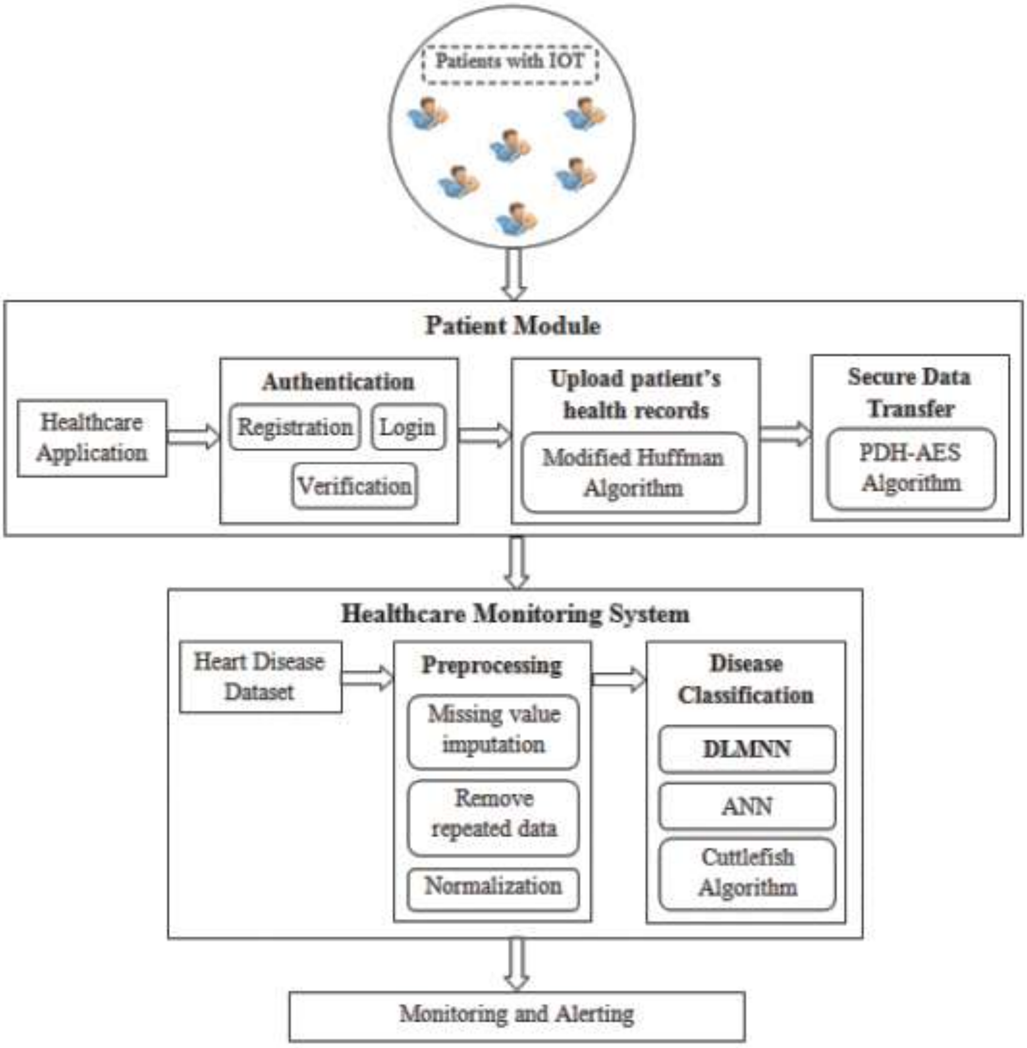

Figure 20: Proposed methodology [118]

- The research conducted by Akter et al. (2021) [119] outlines a healthcare architecture based on CPS (Cyber-Physical Systems). Furthermore, this paper introduces a method for analyzing real-time data to inform future strategic decision-making using a range of machine learning methods. In order to have a comprehensive understanding of the proposed technique in actual implementation, a case study focusing on heart disease is being considered. Consequently, Kaggle resources are employed to collect a dataset on cardiovascular disease. Subsequently, a heart disease prediction model is developed by employing the collected dataset and integrating diverse machine learning classifiers. Binomial logistic regression, decision tree classifier, adaptive boosting, naive Bayes, K-nearest neighbors, and random forest are among the classifier models used. The results of the prediction model and the empirical experiments align quite closely, and the decision tree classifiers demonstrate an accuracy rate of approximately 87%. The suggested model has superior accuracy in predicting future decisions when compared to other models of the same generation. Furthermore, compared to other classifiers, the decision tree classifier demonstrated the highest level of accuracy in predicting heart disease. Using this model for diagnosis can speed up the process, improve accuracy, and assist patients in forecasting heart conditions. Zing this model for diagnosis will expedite the process, enhance accuracy, and aid patients in predicting heart conditions. This model outperforms other existing models in comparison to them.

- The temporal association rules of the Naïve Bayes classification model are a valuable tool for detecting heart disorders, according to the research conducted by Orphanou et al. (2018) [121]. This research study utilized temporal abstraction to pre-process the dataset. By considering the possible recurrence of each TAR pattern in relation to relevant medical history, an accuracy of 86% is attained.
- Arooj et al. (2022) [122] employ a deep learning technique that relies on picture categorization to detect cardiac problems. The complete process of the suggested methodology is outlined in Figure 21. The dataset used in this study is the heart-disease dataset obtained from the public UCI repository. The dataset consists of fourteen distinct features and encompasses data from 1,500 patients. The feature vector serves as an input to the system, enabling the suggested model to determine if the provided patient data belongs to the heart disease class or the healthy class. This categorization is created by utilizing the gathered achievable characteristics from the dataset. They evaluated the efficacy of the proposed approach using various performance metrics, such as F1 score, recall, precision, and accuracy. The generated model had a validated accuracy of 91.7 percent.

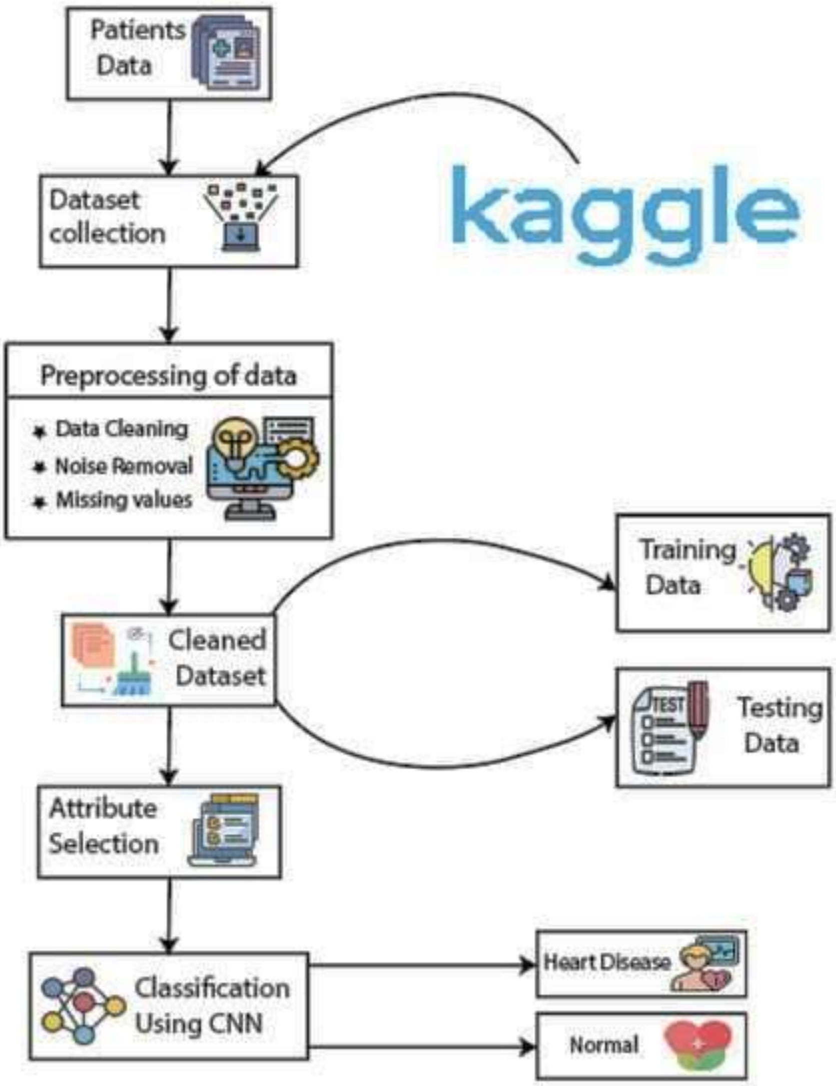

Figure 21: Procedure of proposed methodology [122]

- In the study of Sarra et al. (2022) [123], an improved model was used to lessen the computational load and improve the accuracy of heart disease diagnosis and prediction as shown in Figure 22. A classification model based on the ML algorithm was utilized to improve heart disease diagnosis named a support vector machine. The model is developed using two datasets, and as per the experimental results, the accuracy using the Statlog dataset is 89.7%, which is way more than the Cleveland dataset. Additionally, the number of features present in the dataset also decreased to six from fourteen, which implies the reduction of computational load as well.

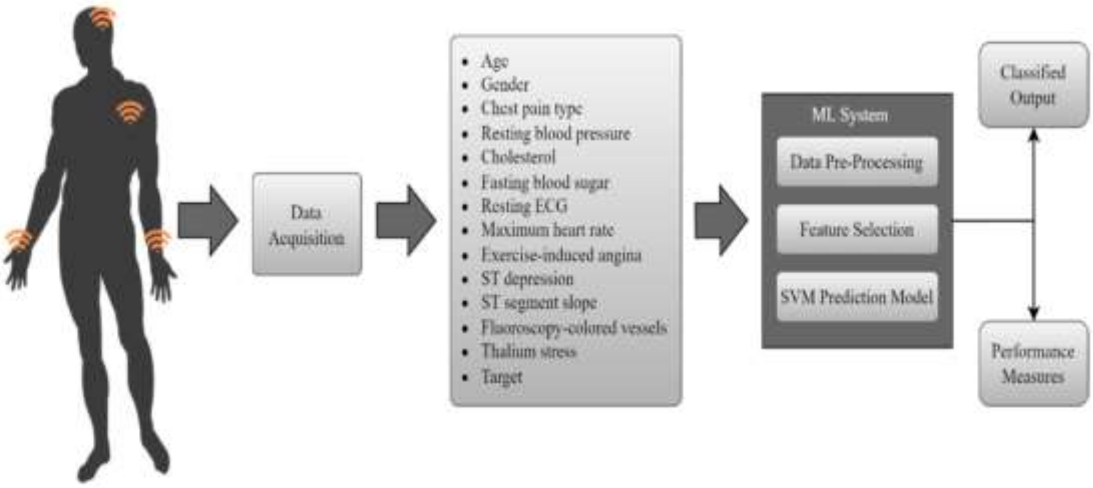

Figure 22: Working procedure of proposed model [123]

Table 4: Comparison of different existing research work for the detection of heart disease

#	Author Name	Year	Method	Input Variables	Output	Remarks
1.	Chang et al. [113]	2022	Random Forest	Fourteen characteristics	Identification of heart disease	Classification Accuracy : 83%
2.	Chicco & Jurman [23]	2020	Gradient boosting, Naive Bayes, kNN, SVM, Artificial Neural Network, decision tree, random forest, and linear regression	Ejection fraction and serum creatinine	Rank the selected features and detect heart failure	The random forest classifier has the highest accuracy, i.e., 74 %
3.	Kumar et al.	2021	Quantum-	Fourteen v	Detectio	Quantum

	[114]		enhanced machine learning approaches	ariables	n of heart failure	random forest has the highest accuracy and shortest execution time, i.e., 150ms
4.	Umer et al. [115]	2022	Deep learning techniques	thirteen characteristics	Prediction of heart failure	Classification Accuracy : 92.89%
5.	Khan [116]	2020	modified deep convolutional neural network	Fourteen characteristics	Identification of heart disease	MDCNN obtains an accuracy of classification of 98.2%
6.	S & U [124]	2022	Deep learning algorithm	14 attributes	types of heart diseases and their severity	The developed model has 95.12 percent prediction

						accuracy
7.	Kaur [117]	2021	Machine learning	thirteen characteristics	Prediction of heart failure	J48 classifier has the highest accuracy, i.e., 92.56 %.
8.	Sarmah (2020) [118]	2020	IoT-centered Deep Learning Modified Neural Network	76 different features of the disease	Secure data transmission and detection of heart disease	Achieved maximum level of security or 95.87%,
9.	Akter et al. [119]	2021	Various ML methodologies	12 features of the disorder	Classification of normal and abnormal heart conditions	Decision tree classifiers' accuracy is about 87%.
10.	Marimuthu et al. [108]	2018	Review	Not Defined	Not Defined	Compared number of approaches but SVM

						outperforms with 95.56%
11.	Limbitote [110]	2020	Review	Not Defined	Not Defined	Analysis shows that deep learning has 92% accuracy
12.	Pandita [111]	2021	Review	Not Defined	Not Defined	BP neural network performs better with 98.20% accuracy
13.	Nashif et al. [120]	2018	ANN, Simple logistic, Random forest, SVM, Naïve Bayes	13 different attributes	Prediction of cardiovascular disease	SVM has highest accuracy i.e., 97.53%
14.	Hazra et al. [125]	2017	Review	Not defined	Not defined	Among all research work, decision tree makes more

						accuracy in classifying disease i.e., 99.2%.
15.	Patel et al. [126]	2015	J48, Random forest, Logistic model tree algorithm	13 different attributes (UCI dataset)	Heart prediction system	J48 algorithm provided highest accuracy i.e., 56.76%
16.	Ganesan and Sivakumar [127]	2019	SVM, MLP, LR and J48	13 different attributes (UCI dataset)	Heart prediction system	Highest accuracy is provided by J48 algorithm which is 91.48%
17.	Orphanou et al. [121]	2018	Naïve Bayes along with TARs	Exercise, diet, age, cholesterol, HDL, triglycerides, LDL, BMI,	Detection of heart disease	Classification accuracy is 86%

				family history related to heart disorder, glucose level, blood pressure, medicines taking, smoking		
18.	Arooj et al. [122]	2022	Deep convolutional neural network	13 attributes	Heart disease predictio n	Classifica tion accuracy is 91.7%
19.	Sarra et al. [123]	2022	SVM	14 attributes from Cleveland dataset	Heart disease classific ation	Classifica tion accuracy is 89.7%

2.2.1 Heart Disease Detection Techniques

Heart disease remains a leading cause of morbidity and mortality worldwide, necessitating effective diagnostic methods to enhance early detection and intervention. Traditionally, the diagnosis of heart diseases relies on various clinical techniques, such as electrocardiograms (ECG), stress tests, and imaging modalities like echocardiography and coronary angiography of these techniques offers unique insights into the cardiovascular system's structure and function but also presents limitations that may affect diagnostic accuracy.

- Electrocardiograms (ECG) are among the most commonly used diagnostic tools for detecting cardiac abnormalities, such as arrhythmias and myocardial infarctions. ECGs measure the heart's electrical activity and provide critical information regarding heart rhythm and conduction pathways. However, ECGs have limitations in detecting certain heart conditions, particularly those not associated with electrical abnormalities. For instance, they may not effectively identify structural heart diseases or early-stage coronary artery disease without significant ischemic changes (Lincy et al. [128]).

- Stress tests, including exercise stress tests and pharmacological stress testing, evaluate the heart's response to physical exertion or medication-induced stress. These tests help identify ischemic heart disease by revealing areas of reduced blood flow to the heart muscle. While stress tests can detect significant coronary artery blockages, their sensitivity and specificity may be limited, particularly in patients with atypical symptoms or those unable to achieve adequate exercise levels. Additionally, false positives and negatives can occur, leading to misdiagnosis or unnecessary further testing (Karna et al. [129]). Additionally, false positives and negatives can occur, leading to misdiagnosis or unnecessary further testing (Karna et al. [129]).

- Imaging techniques, such as echocardiography and coronary angiography, provide detailed visualization of heart structures and blood vessels. Echocardiography uses ultrasound waves to assess cardiac function, valve abnormalities, and structural defects. Coronary angiography, considered the gold standard for diagnosing coronary artery disease, involves the injection of contrast dye into the coronary arteries to identify blockages. Despite their diagnostic value, these imaging methods have inherent limitations. Arteriography's accuracy can be affected by patient body habitus and operator expertise, while coronary angiography is an invasive procedure with associated risks and high costs (Rahman et al. [130]).

- Manual and rule-based diagnostic systems, which rely heavily on clinician expertise and predefined criteria, also face several challenges. These systems are prone to human error, subjective interpretation, and variability in clinical judgment. For instance, two clinicians may interpret the same ECG or imaging result differently, leading to inconsistent diagnoses. Moreover, rule-based systems may not account for the complex interplay of multiple risk factors and clinical variables, limiting their ability to provide comprehensive and accurate assessments (Alqaysi et al. [131]).

- The integration of advanced technologies, such as the Internet of Medical Things (IoMT) and adaptive neuro-fuzzy inference systems (ANFIS), are transforming traditional diagnostic approaches. IoMT enables real-time monitoring and data collection from various health parameters, improving the timeliness and accuracy of heart disease detection. For example, IoMT devices can continuously track heart rate, blood pressure, and other vital signs, providing valuable data for early diagnosis and intervention. ANFIS, combining neural networks' learning capabilities with fuzzy logic's interpretability, offers robust tools for handling the inherent uncertainties in medical data, enhancing diagnostic precision (Mottahedin et al. [132]).

- Despite these advancements, challenges remain in fully integrating these technologies into routine clinical practice. Issues such as data privacy, interoperability of devices, and the need for standardized protocols must be addressed to maximize the benefits of IoMT and ANFIS in heart disease diagnosis. Additionally, while machine learning and deep learning models show promise in improving diagnostic accuracy, they require extensive validation and training on diverse datasets to ensure reliability and generalizability across different patient populations (Zhang and Chen [133]).

2.2.2 Machine Learning Approaches in Heart Disease Prediction

The field of heart disease prediction has significantly benefited from the application of machine learning (ML) models, including logistic regression (LR), support vector machines (SVM), decision trees (DT), and random forests (RF). Each of these models brings unique strengths to the table in diagnosing cardiovascular diseases (CVDs), enhancing both the speed and accuracy of predictions.

Logistic regression remains one of the most widely used models for binary classification tasks, such as heart disease prediction, due to its simplicity and interpretability. However, its linear nature limits its performance in capturing complex relationships among variables. Support Vector Machines (SVMs) are effective in handling high-dimensional spaces and are known for their robustness in classification tasks. They also provide clear visualization of decision-making processes, making them valuable for clinicians who need to understand the rationale behind predictions. Random forests, an ensemble method, combine multiple decision trees to improve predictive accuracy and control overfitting, a common issue in ML models.

- Performance benchmarks indicate that these ML models achieve varying degrees of accuracy in heart disease prediction. Osman Taylan et al. [134] found that the Adaptive Neuro-Fuzzy Inference System (ANFIS) had a prediction accuracy of 96.56%, which was better than the Support Vector Regression (SVR), which had an accuracy of 91.95%. Other models like ANN-CG and ANN-BFG had lower accuracies of 82.37% and 80.79%, respectively. Models, such as ANN-CG and ANN-BFG, showed lower prediction accuracies of 82.37% and 80.79%, respectively. The study highlights that while traditional ML models like LR and SVM can achieve respectable accuracies (up to 91% for LR and 90% for SVM), hybrid models incorporating neuro-fuzzy systems tend to outperform due to their ability to handle complex, nonlinear relationships in data.

  - Challenges faced by ML models in heart disease prediction include overfitting, especially when models are trained on small or imbalanced datasets. Overfitting causes models to perform well on training data but poorly on unseen data, thereby limiting their clinical applicability. The issue of interpretability is another significant challenge, particularly with complex models like deep neural networks and ensemble methods. This "black-box" nature makes it difficult for clinicians to trust and adopt these models in practice. Furthermore, the heterogeneity of medical data, including variations in patient demographics, clinical measurements, and data collection methods, adds another layer of complexity to developing robust ML models. To address these challenges, recent studies have explored hybrid approaches that combine the strengths of different models. For instance, the study by Fatma Taher et al. [135] introduced a hybrid fuzzy fusion classification model for cardiac arrhythmia diseases, achieving accuracies of 98.5% and 98.9% for binary and categorized class modes, respectively. Similarly, Babu Kumar et al. [136] proposed a hybrid feature selection and classification model using ECG signals, demonstrating the potential of integrating modified optimization algorithms with ML models to improve prediction accuracy.

- Despite the promising results, the field continues to grapple with issues related to model generalizability and the need for extensive validation across diverse patient populations. The study by Ahmed A. El-Douh et al. [137] emphasized the importance of feature selection and the use of association rules to enhance model performance, achieving 100% accuracy with RF and DT models. However, the variability in performance across different models and datasets underscores the necessity for ongoing research and development to refine these techniques.

2.2.3 Fuzzy Logic in Medical Diagnostics

Fuzzy logic, introduced by Lotfi Zadeh in 1965, is a mathematical approach that deals with imprecision and uncertainty, making it particularly useful in medical diagnostics where patient data often contains ambiguities. In contrast to classical binary logic, which operates in black-and-white terms (true or false), fuzzy logic allows for degrees of truth, enabling more nuanced interpretations of medical data. This characteristic is especially beneficial in healthcare, where symptoms and diagnostic indicators may not always conform to strict binary categories.

- In the context of diabetes diagnosis, fuzzy logic plays a pivotal role in handling the uncertainty inherent in medical data. For instance, Shrinivasan et al. [138] utilized a Type-2 fuzzy expert system combined with an adaptive neuro-fuzzy inference system (ANFIS) to enhance the classification and prediction accuracy for early-stage diabetes detection. By processing ambiguous data related to glucose levels and other health indicators, the fuzzy system provided more accurate and reliable diagnostic outcomes compared to traditional methods.
- Similarly, in the realm of heart disease prediction, fuzzy logic has proven invaluable. Venkatesh et al. [139] integrated fuzzy logic with machine learning models to predict

heart disease risk more accurately. Their hybrid approach involved using deep learning to extract complex features from patient data, followed by fuzzy logic-based ensemble learning to refine the final predictions. This combination addressed the limitations of conventional models, offering improved accuracy and computational efficiency.

- Fuzzy logic's applications extend beyond disease prediction to include real-time monitoring and risk assessment. Cuevas-Chávez et al. [140] highlighted how IoT and IoMT technologies, when integrated with fuzzy logic systems, can monitor cardiovascular conditions in real-time, providing continuous feedback to healthcare providers. This integration allows for dynamic risk assessment, enabling timely interventions based on fluctuating patient conditions.
- In South Asian countries, where healthcare resources may be limited, fuzzy logic has shown promise in improving diagnostic capabilities. Thakur et al. [141] reviewed the use of fuzzy logic and other soft computing techniques in cardiovascular disease monitoring, noting that fuzzy logic-based models achieved high accuracy rates, making them suitable for deployment in resource-constrained environments.
- Kaur and Khehra [142] further emphasized the versatility of fuzzy logic in detecting heart disease risks. Their review of hybrid approaches, combining fuzzy logic with genetic algorithms and neural networks, demonstrated how these systems could improve diagnostic accuracy and support healthcare professionals in making informed decisions.
- The adaptability of fuzzy logic in handling dynamic and complex medical data is also evident in the work of Bhagat et al. [143], who explored its application in diagnosing heart diseases using wearable health devices. By processing continuous streams of physiological data, fuzzy systems provided real-time diagnostics, enhancing patient care and enabling timely medical interventions.
    - In the specific context of heart failure prediction, Khaleela and Chiada [144] applied neuro-fuzzy systems to predict patient outcomes based on key features like serum creatinine and ejection fraction. Their model achieved 100% accuracy when these features were combined, underscoring the potential of fuzzy logic in critical care scenarios.

- Alasaady et al. [145] extended the application of fuzzy logic to diabetes diagnosis, utilizing ANFIS to process complex patient data and achieve high classification accuracy. Their multistage approach, which included data normalization and anomaly detection, demonstrated the robustness of fuzzy systems in handling diverse medical datasets.
- Lastly, Jha et al. [146] developed a neural fuzzy hybrid system to predict heart attack probabilities. By integrating over 13,000 fuzzification rules, their model provided detailed risk assessments, enabling preventive measures and improving patient outcomes. The system's high accuracy (94%) highlights the potential of fuzzy logic in enhancing diagnostic precision and supporting proactive healthcare management.

2.2.4 Neural Networks for Medical Predictions

Artificial Neural Networks (ANNs) have significantly impacted healthcare by enhancing the prediction and diagnosis of various diseases. Their capacity to model complex, non-linear relationships within large datasets makes them particularly effective in medical applications where traditional methods may fall short. Verma et al. [147] demonstrated this by integrating ANNs with fuzzy logic and the Ant Lion Optimization algorithm to create an optimized neuro-fuzzy-based regression tree framework. This hybrid model showed high accuracy in predicting diseases, particularly heart conditions, by effectively handling complex and imprecise medical data.

- Deep learning models, a subset of ANNs, have also been applied to predict co-morbidities in patients with chronic conditions. Mohamed et al. [148] designed an intelligent model for predicting coronary heart disease and chronic kidney disease in diabetic patients. By using Gated Recurrent Units (GRUs) combined with optimization algorithms, their model effectively identifies risk factors, which is crucial for early intervention and management.

- Real-time monitoring and prediction are other key advantages of ANNs in healthcare. The integration of IoT and cloud technologies enables continuous monitoring of patient health, as demonstrated by Angel Nancy et al. [149], whose

Bi-LSTM-based system provided real-time heart disease risk assessments using data from IoT devices. ANNs are also adaptable and capable of continuous learning, meaning they can be retrained with new data to reflect evolving medical knowledge and patient populations. This makes them suitable for dynamic healthcare environments, such as tracking disease outbreaks or personalizing treatment plans.

- Despite these advantages, there are challenges associated with using ANNs in heart disease detection. The performance of these models heavily depends on the quality and availability of training data. Inconsistent, incomplete, or biased datasets can lead to inaccurate predictions. Mohamed et al. [148] highlighted the importance of comprehensive datasets for improving the robustness of deep learning models in predicting co-morbidities in diabetic patients. Another significant challenge is the interpretability and transparency of neural networks. Often criticized as "black boxes," ANNs can make it difficult to understand how specific predictions are made, which can hinder their acceptance in clinical settings where understanding the rationale behind a diagnosis is crucial.

- Computational complexity and resource requirements also pose barriers to the widespread adoption of ANNs in healthcare. Training deep neural networks requires significant computational power and time, which can be challenging in resource-constrained environments. Verma et al. [147] noted the high resource usage and time consumption in their neuro-fuzzy model, suggesting the need for more efficient architectures to make these systems more accessible. Furthermore, integrating ANN-based systems into clinical workflows requires careful planning to ensure interoperability with existing electronic health record systems and ease of use for healthcare professionals.

2.2.5. Neuro-Fuzzy Systems in Healthcare Applications

Neuro-fuzzy systems have emerged as powerful tools in healthcare applications, blending the learning capabilities of neural networks with the interpretability of fuzzy logic to handle the uncertainty and complexity inherent in medical data. These hybrid models have been extensively researched for their diagnostic potential across various medical domains.

- In the domain of mental health, Kumara et al. [150] introduced Depress-DCNF, a deep convolutional neuro-fuzzy model designed to detect depression episodes using data from Internet of Medical Things (IoMT) devices. The model integrates convolutional neural networks (CNNs) for feature extraction with an adaptive neuro-fuzzy inference system (ANFIS) to classify depressive states. The hybrid model demonstrated superior accuracy (85.10%) compared to traditional deep learning models, emphasizing the value of incorporating fuzzy logic for improved interpretability and decision-making in mental health diagnostics.

- Similarly, Bhanja et al. [151] developed a deep neuro-fuzzy prediction system (DNFPS) for environmental health monitoring, particularly forecasting PM2.5 pollutant concentrations. Their approach combined fully convolutional neural networks (FCNNs) for feature extraction with type-2 fuzzy time series forecasting, optimized using the butterfly optimization algorithm (BOA). While not directly medical, the model's focus on air quality prediction underscores its relevance to public health, given the known cardiovascular and respiratory risks associated with PM2.5 exposure. The DNFPS model outperformed traditional models like ARIMA and SVR, highlighting the efficiency of neuro-fuzzy systems in handling complex, time-dependent data.

- In medical data security, Mohiyuddin et al. [152] applied ANFIS to secure cloud storage of Medical IoT (MIoT) data, addressing privacy and integrity concerns. Their hybrid approach first classified medical data using machine learning algorithms and then used ANFIS to enhance cloud security. With a minimal training error and high classification accuracy (up to 97.4% using KNN), the study showcased ANFIS's versatility beyond diagnosis, extending to secure data handling in healthcare systems.

- Specific to cardiovascular disease (CVD) prediction, several studies have demonstrated the efficacy of neuro-fuzzy systems. Saritha et al. [153] reviewed various machine learning approaches for ECG data classification, including fuzzy logic and hybrid algorithms, which have proven effective in the early detection of heart disease. Their findings emphasized the importance of combining fuzzy logic with neural networks to improve diagnostic accuracy and enable real-time monitoring.

CHAPTER 3: PROBLEM FORMULATION & OBJECTIVE

3.1. Problem Formulation

Heart failure affects approximately 26 million individuals worldwide during a global pandemic, and its prevalence is increasing [17]. The expenses associated with heart failure healthcare are substantial and are projected to increase significantly due to the aging population. Despite significant advancements in medicine and prevention, the quality of life remains low, and there have been substantial rates of death and illness. Geographic variations in the rates of morbidity, mortality, incidence, and prevalence have been observed among heart failure patients, based on the different causes and clinical characteristics found. In contrast to Europe, there has been a lack of substantial study undertaken to investigate the impact of heart failure in developing countries such as India. As a result, the understanding of the epidemiology of heart failure in these nations remains incomplete. Practicing internists and cardiologists are well aware of the substantial impact this burden is anticipated to have, considering that India is a country with sixteen percent of the global population and bears twenty-five percent of the burden of coronary heart disease. Furthermore, it is worth noting that there are currently 120 million individuals in this country who are afflicted with hypertension, along with a substantial population of individuals with RHD [19].

Therefore, cardiovascular illnesses represent the primary cause of death for a large number of individuals worldwide [20]. The prediction of cardiovascular illnesses is a hard and difficult process due to various contributing signs such as irregular pulse rate, diabetes, cholesterol level, and excessive blood pressure [21]. Furthermore, the symptoms of various diseases can differ depending on an individual's gender. Research indicates that men with heart disease are more likely to experience chest pain, while women with the same condition are more likely to experience shortness of breath, extreme exhaustion, and nausea instead of chest pain [22]. Various writers and academics have established a range of approaches to predict this life-threatening illness.

However, accurately diagnosing this disease in its early stages is challenging due to various aspects that affect it, including precision, speed of execution, and complexity of the technique [23]. However, if a method has the capability to anticipate it at an initial phase, then the efficient identification and therapy can preserve a substantial amount of patients' lives [24], [25].
Furthermore, accurately predicting the survival of a patient with heart failure is a significant challenge, which is crucial for informing clinicians' decision-making processes. Effective management of a patient with heart failure requires a doctor who possesses the requisite expertise in this specific field. Uncertainty arises from several factors, including limits in the diagnostic technique, the presence of missing data, erroneous patient attributes, and the incapacity of medical practitioners to define the effects and causes of the condition.

In order to overcome this restriction, the field of health extensively employs artificial intelligence techniques, which significantly impact global health outcomes. Health experts are widely utilizing the multiple advantages of these approaches, resulting in a substantial improvement in the healthcare industry. This project utilizes machine learning techniques to create and develop a concurrent health monitoring system based on ML technology. These devices also aid in the early detection of heart failure, enabling timely and effective treatment to prevent the worsening of the patient's condition. Therefore, this approach will effectively meet the requirement of early identification of heart failure.

3.2. Objective of the study

The objectives of the research work are as follows:

1. To study and analyze the existing fuzzy inference systems for heart disease.

2. To collect and preprocess the data of Heart Patients.

3. To develop an intelligent hybrid inference system for monitoring of heart diseases.

4. To compare the performance of the proposed system with existing systems.

3.3. Rationale for Feature and Model Selection

The effectiveness of any predictive system is fundamentally dependent on two key decisions: the selection of relevant input features and the choice of an appropriate modeling technique. This section provides the rationale for these choices in the context of developing the heart disease monitoring system.

3.3.1 Basis for Feature Selection

The input variables for the proposed models were chosen based on their established clinical significance as primary risk factors for cardiovascular disease. The seven selected features Cholesterol, Blood Pressure, Diabetes, Irregular Heartbeat, Smoking, Shortness of Breath, and Age represent a comprehensive set of physiological, lifestyle, and demographic indicators that are widely recognized in medical literature and clinical practice as being highly correlated with the onset and progression of heart conditions. This set of features was refined through a data pre-processing and reduction phase to ensure that only the most impactful variables were used for training the model, thereby minimizing noise and improving computational efficiency. By grounding the feature set in established medical knowledge, the model is built on a foundation of clinically relevant and validated data, enhancing its potential for accurate diagnosis.

3.3.2 Basis for Model Selection

The choice of an Adaptive Neuro-Fuzzy Inference System (ANFIS) as the core methodology for the intelligent hybrid model was driven by the need to address the inherent challenges of medical diagnosis, such as data uncertainty and the need for interpretability. While conventional machine learning models have shown promise, they often present a trade-off between accuracy and transparency. For instance, Artificial Neural Networks (ANNs) excel at identifying complex, non-linear patterns in data but are often considered "black boxes," which can limit their acceptance by clinicians who require a clear rationale for diagnostic decisions.

Conversely, fuzzy logic systems are highly interpretable, using linguistic variables and IF-THEN rules that mimic human reasoning, making them ideal for handling the imprecision common in clinical data. The ANFIS model was selected because it combines the strengths of both approaches. It leverages the learning capability of neural networks to automatically tune the parameters of the fuzzy inference system from data, while retaining the interpretable structure of fuzzy logic. This synergy allows the system to be both highly accurate in its predictions and transparent in its decision-making process, making it a superior choice for a clinical decision support tool.

CHAPTER 4: DATA COLLECTION AND PRE-PROCESSING

As discussed in chapter 1, machine learning is a methodology which allows a system or computer to act like a human being and improve itself from its learning and experiences even without any kind of explicit programs. Additionally, the training of every model developed by using ML technology is specifically relying on the data or input provided to learn from it. Hence, this makes the data an essential component which is required in the development of any ML model effectively. The main aspects or steps by using which an intelligent model is developed are shown in figure 23

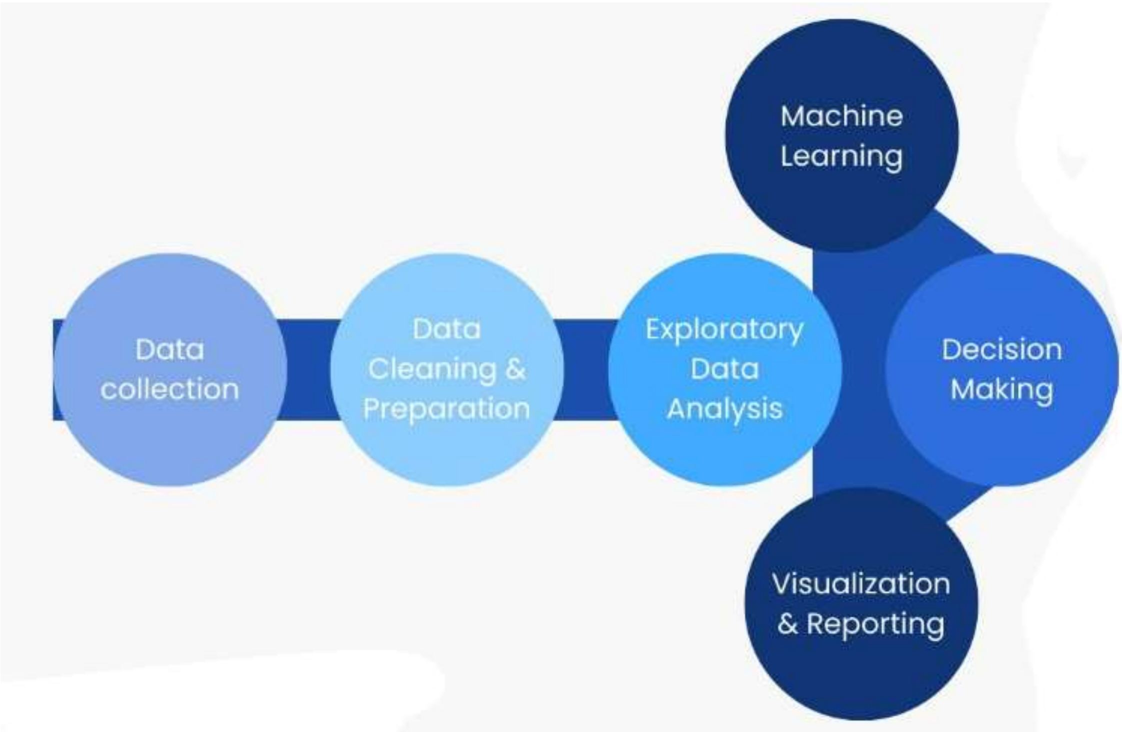

Figure 23: General steps for the development of ML model [154]

Hence, from the above diagram, it is crystal clear that the most essential and significant steps of developing a ML model is data collection and data pre-processing.

It cannot be false to say ML cannot be able to learn or survive without data. The main way to enter into ML model development is the data collection stage. If the gathered data is incorrect then it is difficult to achieve the goal by training the model. Therefore, the most primitive aspect of the whole process of development is data collection and pre-processing and these steps must be executed correctly.

4.1. Data Collection

In the process of developing an intelligent model utilizing ML, the first and foremost step is data collection. The prediction capacity of a system is directly proportional to the dataset accuracy. This means that if the gathered data is accurate which is further used in the training phase of the system, then the prediction or result generated by the system will also be correct and accurate. The issues that arise while acquiring the data for any specific problem are as follow [154]:

Data Bias: The algorithm could encourage inherent biases on issues like sex, age, or geography based on how the data & its labels have been chosen. It is challenging to identify and eliminate data bias.

Data imbalance: There may be an unusually large or small amount of comparable samples for some classifications in the data. Such issues run the danger of being underrepresented in the model as a result.

Missing data: There might not be any sub-data. For a certain kind of prediction, that could appear as blank or missing value in the columns.

Inaccurate data: The data gathered might not have anything to do with the problem statement.

There are various techniques which can be applied or used to resolve the above-mentioned issues in data collections. These are:

Custom data: Some organizations produce or acquire the data and give it to the needful engineer for a price.

Private data: in some cases, the ML engineers make the data on their own. When there isn't much data needed to train the model and the problem is too specialized to generalize to an open-source dataset, this technique of data collection is useful.

Web scraping & crawling: Websites can be crawled and scraped for information using automated bots or tools.

Publicly downloadable, pre-cleaned data: Utilizing existing open-source expertise is useful for gathering data if the problem statement aligns with a clear, pre-existing, and well-structured dataset.

Figure 24: Techniques of data collection [155]

For this particular research, the data collection method aligns with the private/in-house approach. A dataset comprising 800 patient samples was gathered directly in consultation with a heart specialist. This method was chosen to ensure the clinical relevance and quality of the data, as the problem of heart disease diagnosis is highly specialized and benefits from expert-curated information.

4.2. Data Pre-processing

Before creating a model using any selected attributes in the data collection process, data preparation is required. The main steps that must be followed to pre-process the data before finalizing it are:

Data cleaning: in this technique, the missing values and noisy data is removed from the dataset either by using automation tools or manually. In other words, data cleaning is a technique which is used to eliminate outliers, resolving the inconsistency, calming noisy data and completing missing numbers in the collected data.

- In this study, the data cleaning process was applied to the 800-sample dataset to handle inconsistencies. The primary actions involved filling missing values and removing outliers and noisy data to ensure the integrity of the dataset before model training.

Data transformation: After cleaning the data, the next step is to combine the high-quality data into a new format by altering the structure and values. This can be done by utilizing the various methodologies for data transformations as mentioned in figure 25.

- The transformation technique specifically employed in this research was normalization. All relevant numerical features in the dataset were scaled to a standard range. This was a critical step to prevent attributes with larger scales from dominating the learning process and to ensure all features contributed proportionally to the model's outcome.

Data reduction: Data mining techniques may not be able to handle a data warehouse's dataset because of its scale. Getting an enlarged version of the data set that is significantly less in size but yet yields high-caliber analytical results is one potential option. A large dataset can also affect the processing and memory of a model. Hence, reducing the dataset by using techniques is the best option to opt and it will automatically lead to the higher accuracy of the model.

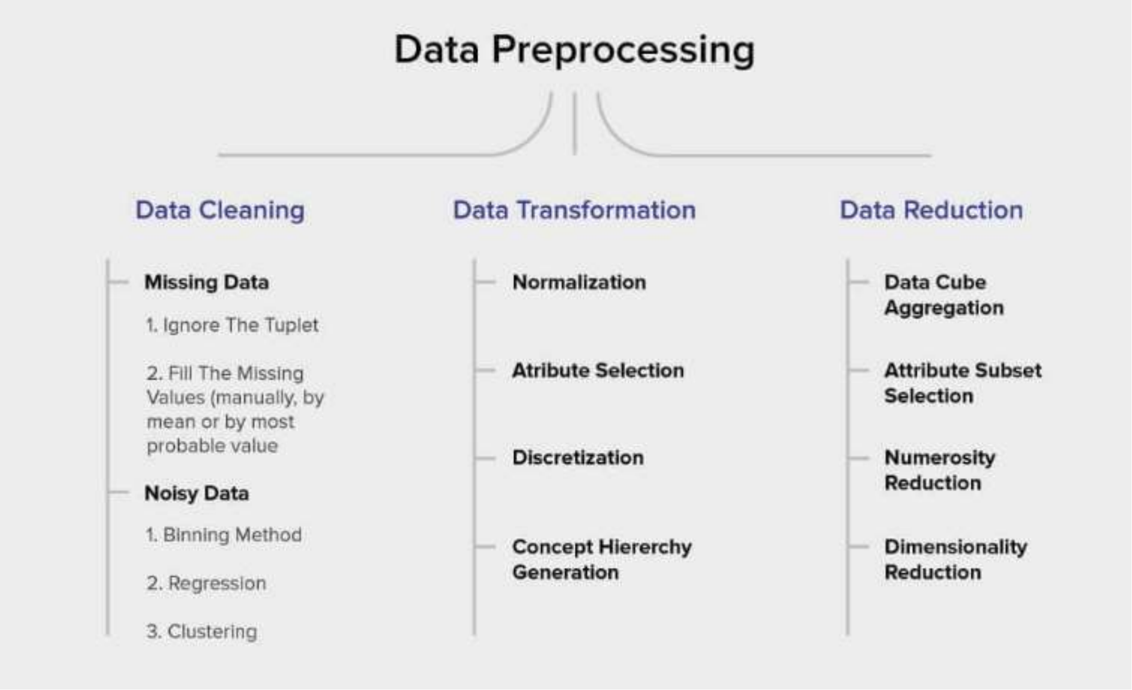

Figure 25: Data Pre-processing techniques [156]

In this research work, the data set of the heart patients has been gathered in which a total 800 data samples are included. The main challenge which is faced while finalizing the dataset for the training phase is the attributes. Hence, in this research work, the data is first cleaned by filling up the missing values, removing outliers and noisy data. After that, the dataset was normalized for data transformation, and finally, its dimensions were reduced. Therefore, the final dataset used for the training and testing phase of the model has only 7 different symptoms or risk factors which have a high contribution in generating heart disease to any individual.

Missing values occur when some data points are not recorded or are unavailable. To handle this, the mean or median of the corresponding feature is calculated from the available data and used to fill in the missing values. The mean is used when the data is fairly symmetric, while the median is preferred when the data is skewed, as it is less affected by extreme values. This approach helps maintain the overall distribution of the data and prevents loss of important records.

Outliers are data values that fall outside the medically acceptable range for a given attribute, such as unrealistic blood pressure or heart rate values. These values are carefully reviewed and removed manually because they are most often caused by data entry mistakes, measurement errors, or noise. Removing such outliers improves data quality and ensures that the model learns from clinically valid and reliable information.

Normalization is the process of scaling the data in a dataset so that all features are on a similar scale before training machine learning models. Many datasets contain features with different units and ranges, such as age, blood pressure, cholesterol, and glucose levels. If these features are used directly, variables with larger values may dominate the learning process and affect model performance.

In normalization, the original values are transformed into a common range, usually between 0 and 1, using methods such as Min–Max scaling. This helps the model treat all features fairly and improves the speed and stability of learning.

Overall, normalization improves model accuracy, reduces bias caused by feature scale differences, and makes the training process more efficient and reliable.

Normalization of the data is done by using Min-Max scaling method. The formula for Min–Max scaling is:

$$X\_scaled = (X - X\_min) / (X\_max - X\_min)$$

Here, X is the original value, X_min is the minimum value of the feature, and X_max is the maximum value of the feature.

This method ensures that the smallest value becomes 0 and the largest value becomes 1, while all other values fall between 0 and 1.

CHAPTER 5: DEVELOPMENT OF A FUZZY EXPERT SYSTEM FOR THE DIAGNOSIS OF HEART DISEASE

5.1. Methodology

In order to identify an exact level or stage of heart disease and offer the paramount system for heart diseases, this research work has presented an expert system using fuzzy logic. The introduced system gathers precise information from the suffering individual by posing some relevant questions. After that, the fuzzy rules are developed on the basis of acquiring information from the doctor, which is then compared with the knowledge base. Later, the developed rules are processed by an essential element of fuzzy logic named the inference engine. This component of the controller matches the rule from the knowledge base, and then the most appropriate rule is fired among all other rules. If provided inputs are not matched with any rules, then the system will automatically reject the input. If an accurate diagnosis is made using the data provided by the user, only then the system will be suggested to doctors to determine the severity of the ailment. When this system completes the diagnosis, then the doctor gives the patient the right dosage of medication. Therefore, a doctor can now suggest a prescription based on the decision provided by a medical expert system.

The development and validation of this fuzzy expert system were based on the 800-sample patient dataset that was collected and pre-processed as detailed in Chapter 4. This dataset, curated in consultation with a heart specialist, provided the clinical basis for defining the fuzzy rules and testing the system's diagnostic accuracy.

The developed system uses 7 different parameters as input and 3 parameters as output. The input variables are cholesterol, blood pressure, and irregular heartbeat, and diabetes, shortness of breath, age and smoking. Similarly, the output given by the system identifies the heart disease and gives a warning to the doctor and patient accordingly. The output variables are the level of the disease, such as healthy, early stage and advanced stage. The entire development has been done in the Mamdani inference method and Matlab software. Figure 26 shows the flow of methodology that is used in the implementation of the medical expert system. Moreover, figure 27 displays the fuzzy classification of the developed system.

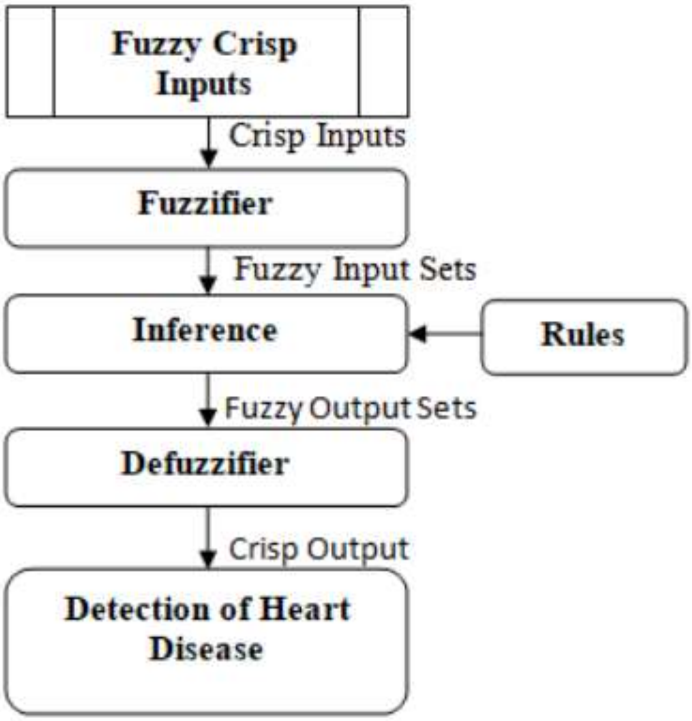

Figure 26: Flowchart of the used methodology

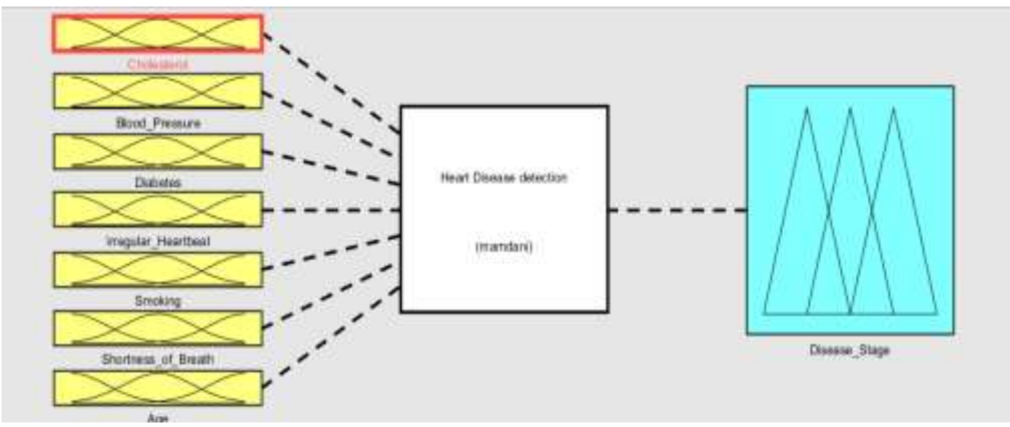

Figure 27: Fuzzy Classification

5.1.1. Input variables

The input variables considered in the developed system are detailed below. To enhance the model's clinical accuracy, the ranges for key physiological inputs like Blood Pressure and Diabetes (Fasting Glucose) have been updated to align with established medical guidelines. A normal resting systolic blood pressure for adults is typically above 90 mmHg, and normal fasting blood glucose is below 100 mg/dL.

Table 5: Input variables with Clinically-Aligned Ranges

Sr. no.	**Input parameters**	**Variable names**	**Membership function**	**Ranges**
I.	Cholesterol	Normal	Trapezoidal	150-200 mg/dL
		Medium	Triangular	190 – 250 mg/dL
		High	Triangular	230 – 320 mg/dL
		Very High	Trapezoidal	280 – 500 mg/dL
II.	Blood Pressure	Normal	Trapezoidal	90- 130 mmHg
		Medium	Triangular	120 – 160 mmHg
		vHigh	Trapezoidal	150 – 200 mmHg

III.	Diabetes	Normal	Trapezoidal	90-160 mg/dL
		Diabetic	Trapezoidal	150 – 400 mg/dL
IV.	Irregular heartbeat	No	Trapezoidal	<0.6
		Yes	Trapezoidal	0.3 – 1.0
V.	Smoking	False	Trapezoidal	<0.6
		True	Trapezoidal	0.3 – 1.0
VI.	Shortness of Breath	No	Trapezoidal	<0.6
		Yes	Trapezoidal	0.3 – 1.0
VII.	Age	Young	Trapezoidal	<38 yrs
		Middle age	Triangular	34 – 45 yrs
		Old	Triangular	40 – 58 yrs
		Very old	Trapezoidal	53 – 75 yrs

The pictorial views of these input variables and their membership functions are presented in figures 28 to 34. The X-axis represents the input variable. It shows the actual numerical values of the variable under study, arranged from lower to higher values. These values are grouped into different linguistic categories such as low, medium, high, or very high, depending on the context of the problem.

The Y-axis represents the degree of membership. Its values range from 0 to 1. A value of 0 indicates that the input value does not belong to a particular category, while a value of 1 indicates full membership. Values between 0 and 1 represent partial membership, meaning the input value can belong to more than one category at the same time.

In general, the X-axis shows the range of input values, and the Y-axis shows how strongly each value belongs to a specific category.

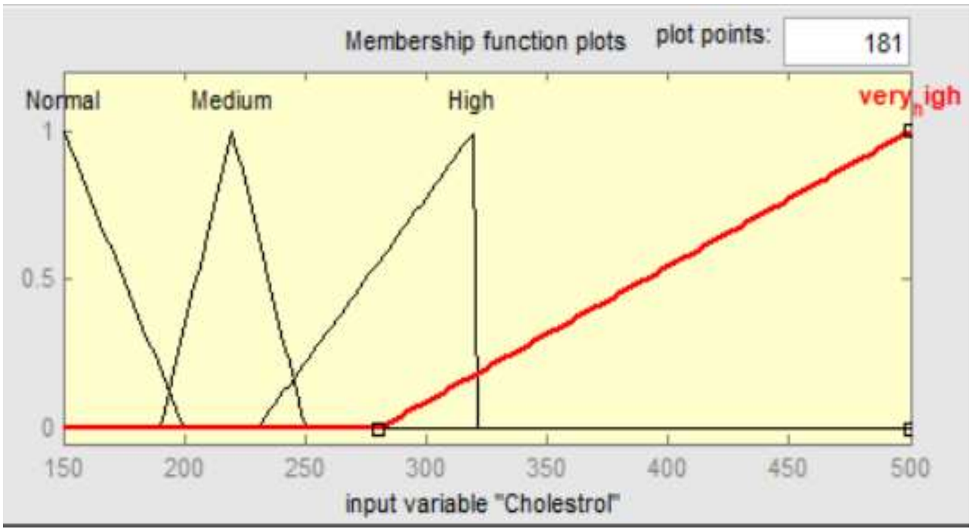

Figure 28: Cholesterol input variable

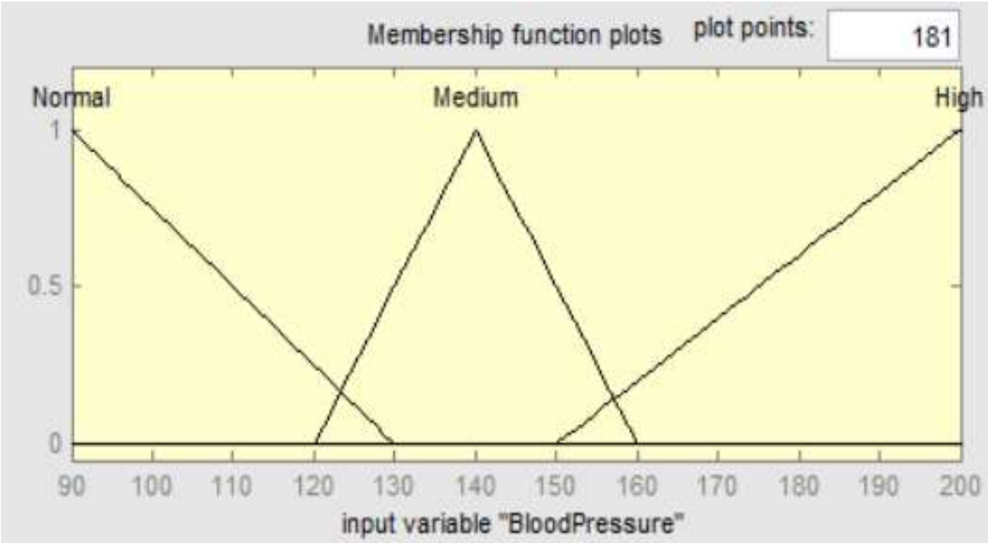

Figure 29: Blood Pressure input variable

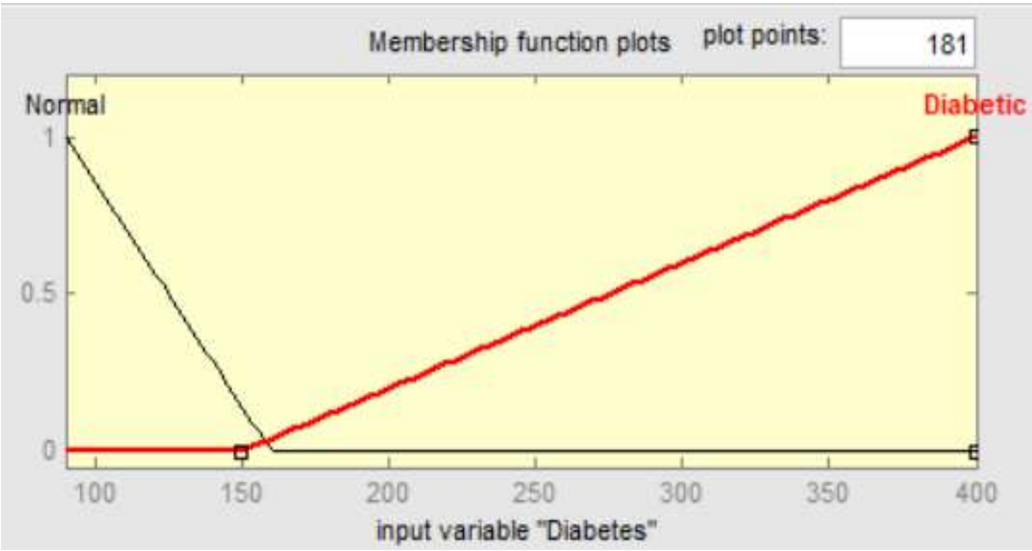

Figure 30: Diabetes Input Variable

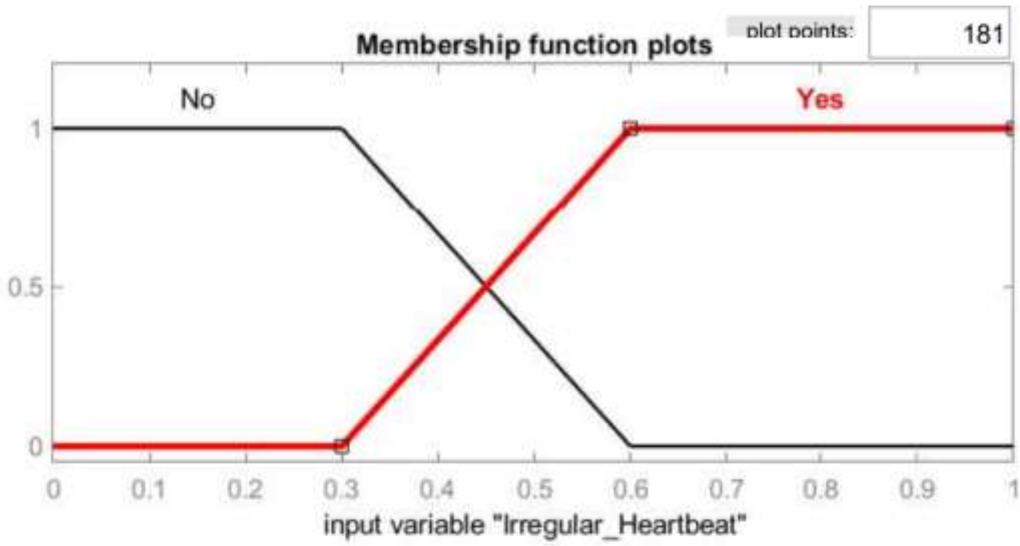

Figure 31: Irregular heartbeat input variable

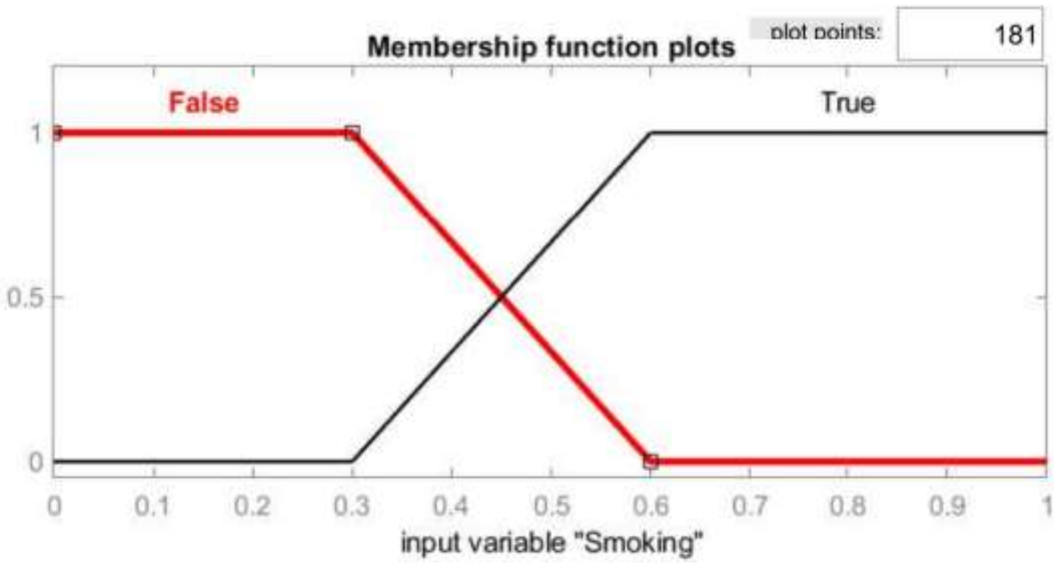

Figure 32: Smoking input variable

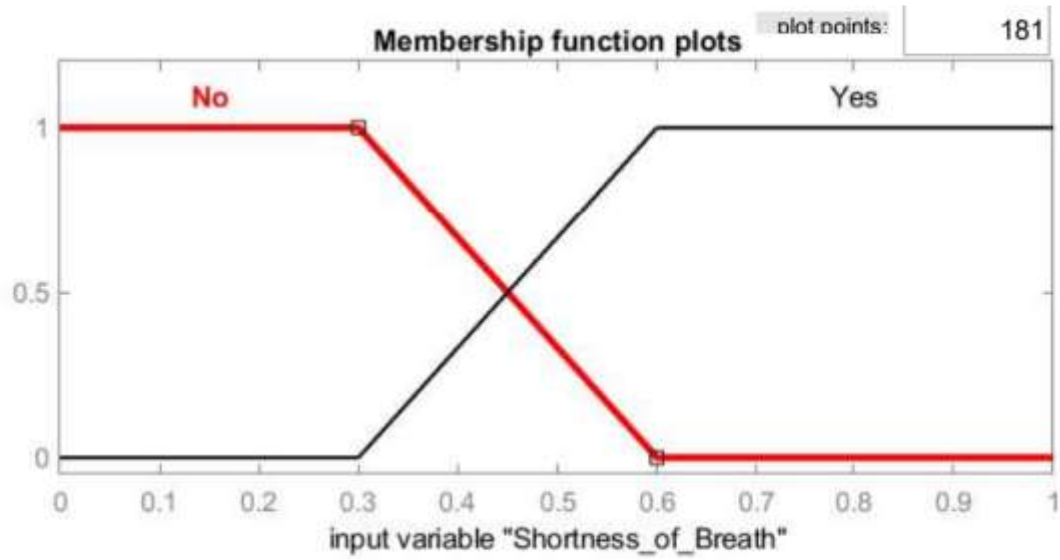

Figure 33: Shortness of Breath Input Variable

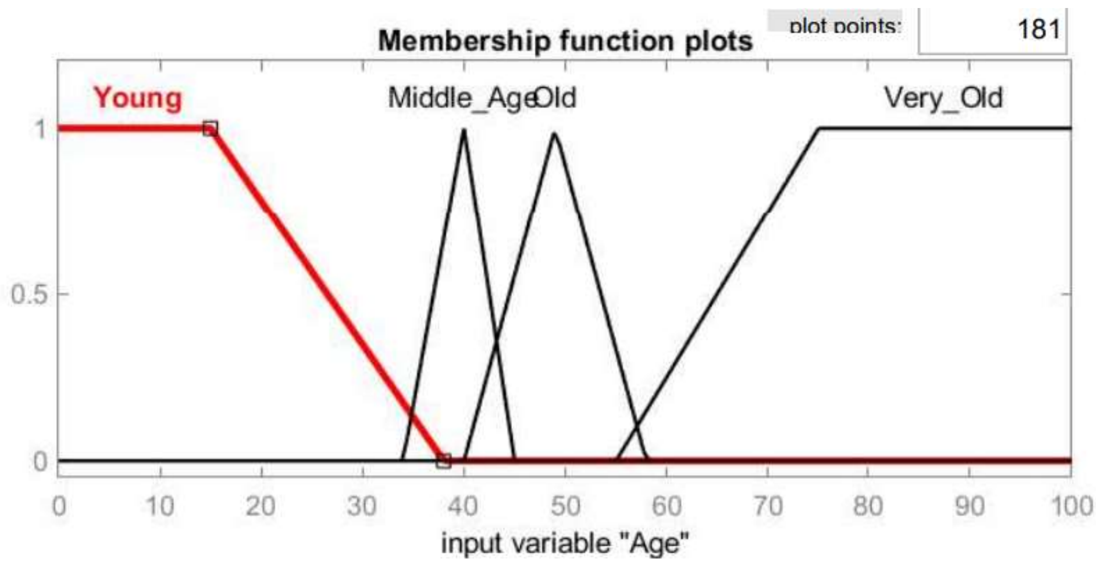

Figure 34: Age input Variable

5.1.2. Output Variables

The output variables that are considered in the developed system are explained in table 6, and also its pictorial view is presented in figure 35.

Table 6: Output Variables

Sr. no.	Output parameters	Variable names	Membership function	Ranges
I.	Disease Stage	Healthy	Trapezoidal	<1.7
		Early Stage	Triangular	1.55 – 2.55
		Advanced Stage	Trapezoidal	2.4 – 4

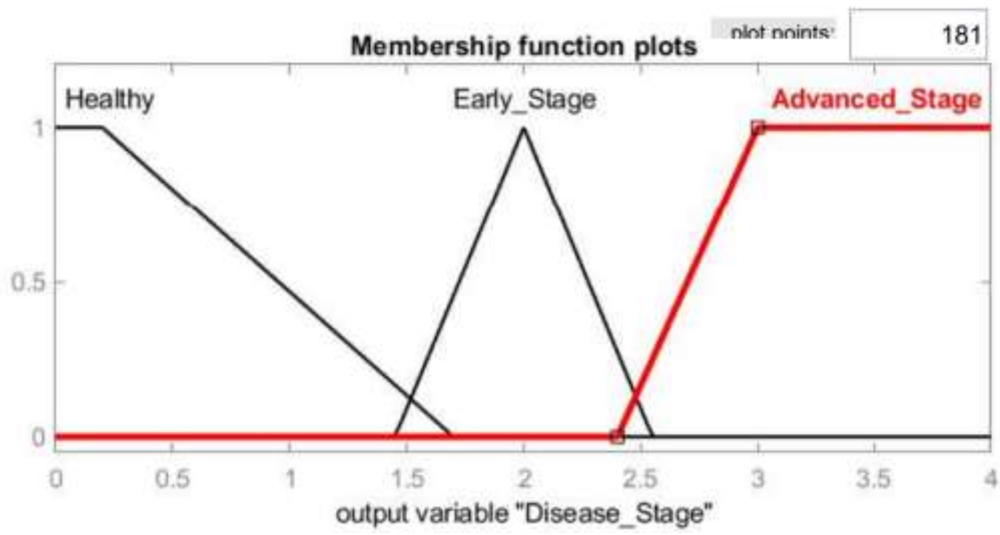

Figure 35: Output variable

5.1.3. Rules

The rule base is the most critical component of the fuzzy inference system, as it encodes the expert knowledge that maps input symptoms to a diagnostic outcome. While a full combinatorial expansion of the input linguistic variables would theoretically generate 768 rules ($4 \times 3 \times 2 \times 2 \times 2 \times 2 \times 4$), creating and managing such a large rule base is computationally inefficient and can lead to model overfitting.

Therefore, a more practical approach was adopted to create a concise and effective rule base. The number of rules was reduced to 50 through a process of expert knowledge elicitation. Working with medical domain knowledge, primarily from consulting with a heart specialist, the most clinically relevant and frequently encountered combinations of risk factors were identified and prioritized. This expert-driven method ensures that the rule base is not just a mathematical construct but a reflection of real-world diagnostic reasoning. This focused set of 50 rules provides comprehensive coverage of the problem domain while remaining computationally efficient and robust. Figure 36 shows the rule viewer of the developed model. The Rule Viewer provides a graphical representation of the fuzzy inference process by displaying the relationship between input variables and the output for a given set of input values. It shows the degree of membership of each input in the corresponding fuzzy sets, the activation strength of each fuzzy rule, and the aggregated output after defuzzification. This visualization helps in validating the correctness of the defined membership functions and fuzzy rules, and ensures that the fuzzy system produces meaningful and consistent outputs for different combinations of input parameters related to heart disease diagnosis.

Figure 36: Rule viewer

5.1.4. Basis for Membership Function Selection

The membership functions (MFs) for the input and output variables were selected to effectively model the inherent imprecision of clinical data while maintaining computational efficiency.

- Triangular Membership Functions were chosen for intermediate linguistic terms (e.g., "Medium High" Cholesterol, "Middle Age"). This shape is computationally simple and is effective for representing concepts where membership is centered on a single peak value and decreases linearly on either side.
- Trapezoidal Membership Functions were used for the lower and upper-end linguistic terms (e.g., "Normal" Blood Pressure, "Very Old" Age). This shape is ideal for representing values that are considered to have full membership over a range or plateau, which accurately models concepts like a "normal" state that holds true across a span of values before beginning to transition into a different state.

This combination of MFs provides a robust framework that balances clinical interpretability with the practical requirements of the fuzzy inference system.

5.2. Chapter Summary

This chapter detailed the development of a medical expert system for the diagnosis of heart disease using the Mamdani fuzzy inference method. It defines the system's architecture, which is based on seven clinical input variables (Cholesterol, Blood Pressure, Diabetes, etc.) and one output variable representing the stage of the disease (Healthy, Early Stage, Advanced Stage). The basis for selecting the triangular and trapezoidal membership functions was explained, and the input ranges were aligned with clinical guidelines. Furthermore, the process of creating an efficient and expert-informed rule base of 50 rules, reduced from a theoretical 768, was justified. This chapter establishes the complete design of the fuzzy expert system, setting the stage for the evaluation of its performance in Chapter 7.

CHAPTER 6: AN INTELLIGENT HYBRID INFERENCE SYSTEM FOR MONITORING OF HEART DISEASE

6.1. Methodology

In order to identify an exact level or stage of heart disease and offer the paramount system for heart diseases, this research work has presented an expert system using fuzzy logic. The introduced system gathers precise information from the suffering individual by posing some relevant questions. After that, the fuzzy rules are developed on the basis of acquiring information from the doctor, which is then compared with the knowledge base [93]. Later, the developed rules are processed by an essential element of fuzzy logic named the inference engine. This component of the controller matches the rule from the knowledge base, and then the most appropriate rule is fired among all other rules. If provided inputs are not matched with any rules, then the system will automatically reject the input. If an accurate diagnosis is made using the data provided by the user, only then the system will be suggested to doctors to determine the severity of the ailment. When this system completes the diagnosis, then the doctor gives the patient the right dosage of medication. Therefore, a doctor can now suggest a prescription based on the decision provided by a medical expert system [155].

- Cholesterol
- Blood pressure
- Diabetes
- Irregular heartbeat
- Smoking
- Shortness of breath
- Age

Similarly, the system is designed to categorize the input data into different stages based on how the condition or situation develops. These stages include the normal stage, which indicates that everything is functioning as expected, the early stage, where initial signs or symptoms may appear, and the advanced stages, which reflect more serious or severe conditions. The system analyzes the provided input values, such as symptoms, measurements, or other relevant data, and processes them to determine which stage applies. After completing this analysis, the system then gives an output that corresponds to the identified stage, helping users to better understand the current state of the condition. This process allows for clear and effective monitoring and early detection of potential issues. The flow of methodology used in the implementation of the developed model is provided in figure 37.

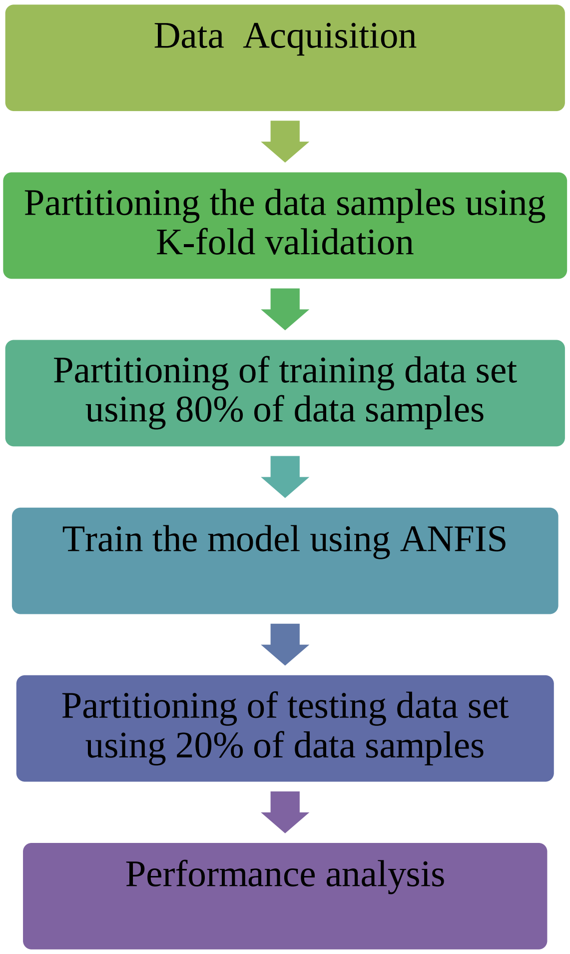

Figure 37: Flow of used methodology

6.2. Development of model

6.2.1. Model structure and input variables

In this study, for input and output variables, the used membership functions are triangular membership functions. There are different numbers of membership functions for each input variable, such as 4 MFs for input 1, i.e., cholesterol, 3 for input 2, i.e., blood pressure, 2 from input 3 to 6, which are diabetes, irregular heartbeat, smoking and shortness of breath and 4 for input 7, i.e., age. The structure of ANFIS is illustrated in table 7 and figure 39. Moreover, the FIS properties of the ANFIS model are also demonstrated in figure 38. The representation of all 7 inputs is shown in figure 40 to 46, respectively. Moreover, table 8 shows the list of input variables with their semantic name, group, number and name.

Table 7: Structure of ANFIS

Structure of ANFIS	
No of layer of ANFIS	5
Number of input variables	7
Name of input variables	• Cholesterol as input 1 • Blood Pressure as input 2 • Diabetes as input 3 • Irregular Heartbeat as input 4 • Smoking as input 5 • Shortness of breath as input 6 • Age as input 7
Type of membership function	Triangular
Number of rules	768
Number of outputs	1

Number of stages of disease	3
Name of stages	• Normal stage • Early stage • Advanced stage

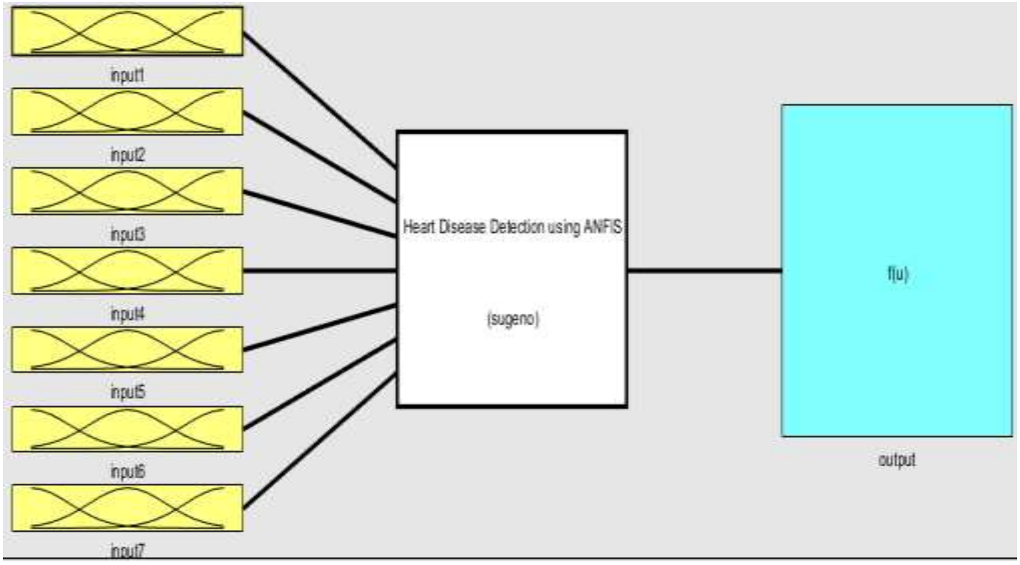

Figure 38: FIS properties of developed intelligent hybrid model

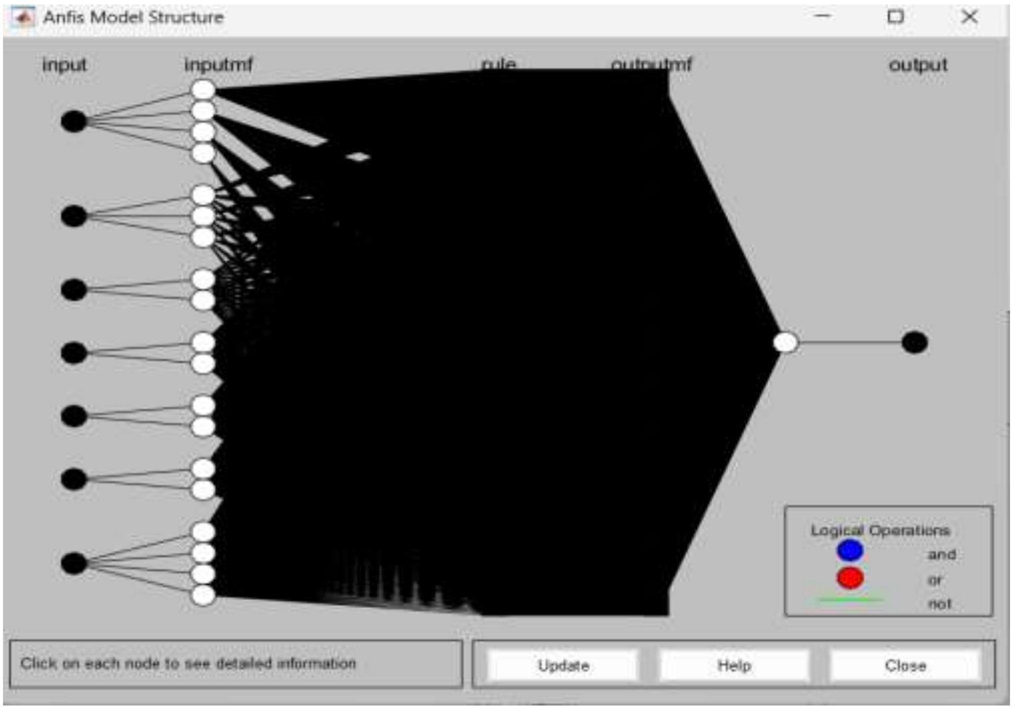

Figure 39: ANFIS model structure

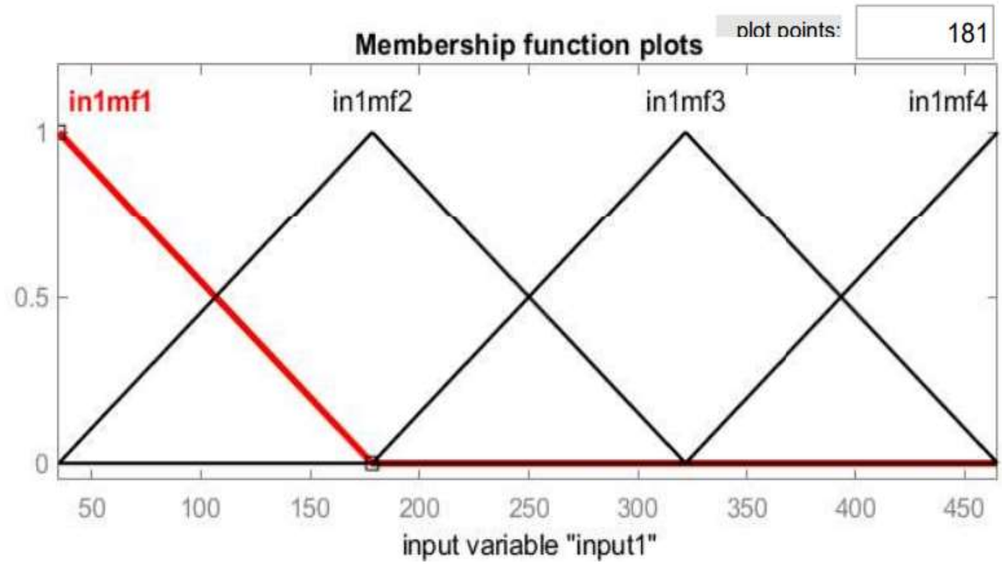

Figure 40: MF plot of input 1

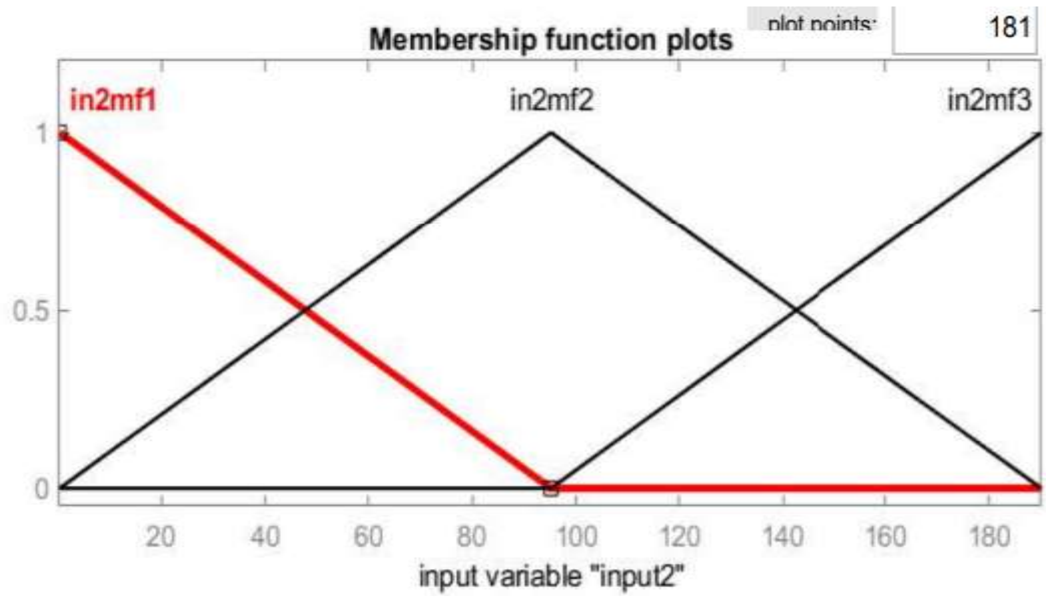

Figure 41: MF plot of input 2

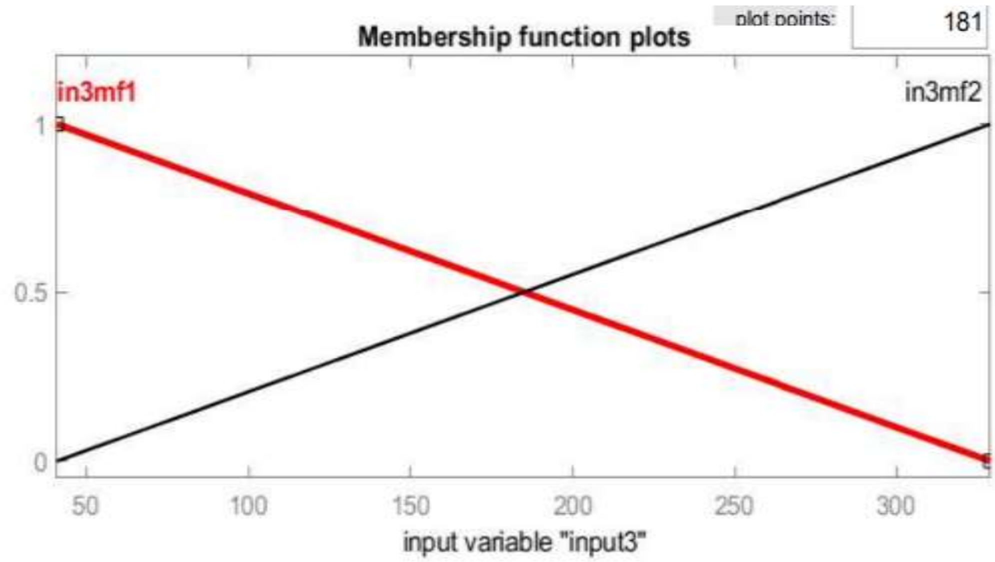

Figure 42: MF plot of input 3

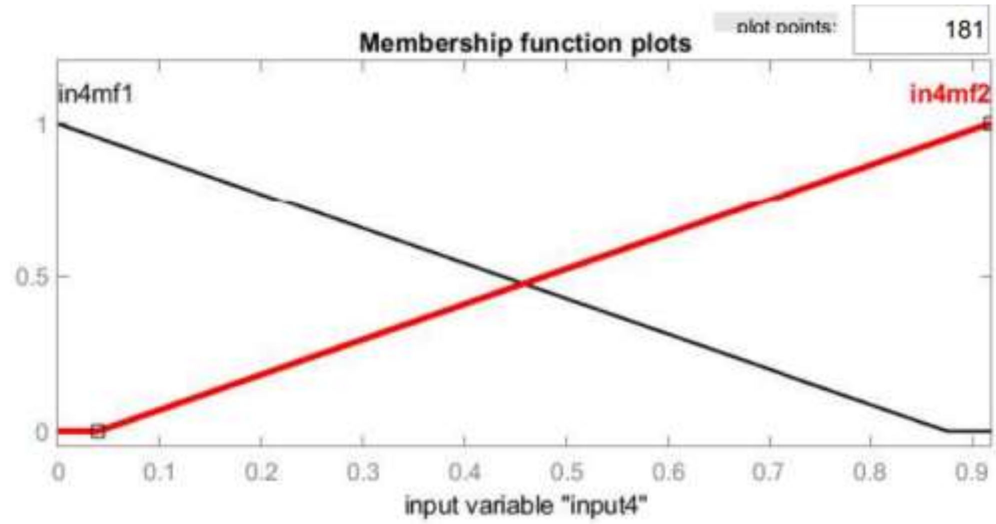

Figure 43: MF plot of input 4

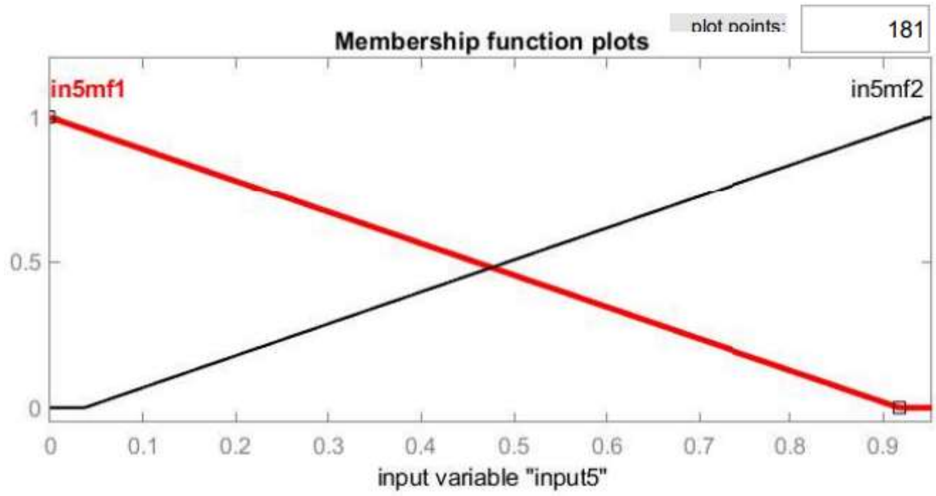

Figure 44: MF plot of input 5

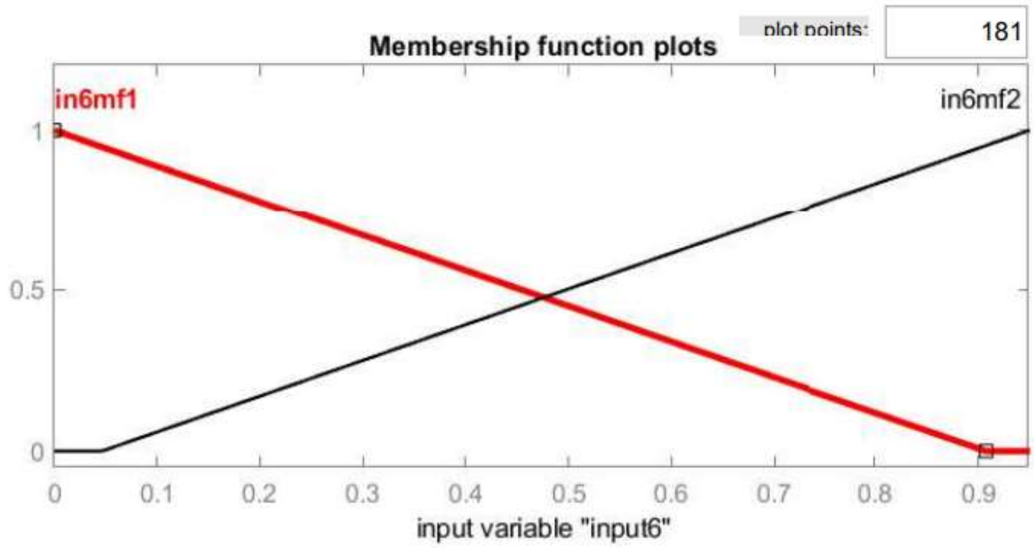

Figure 45: MF plot of input 6

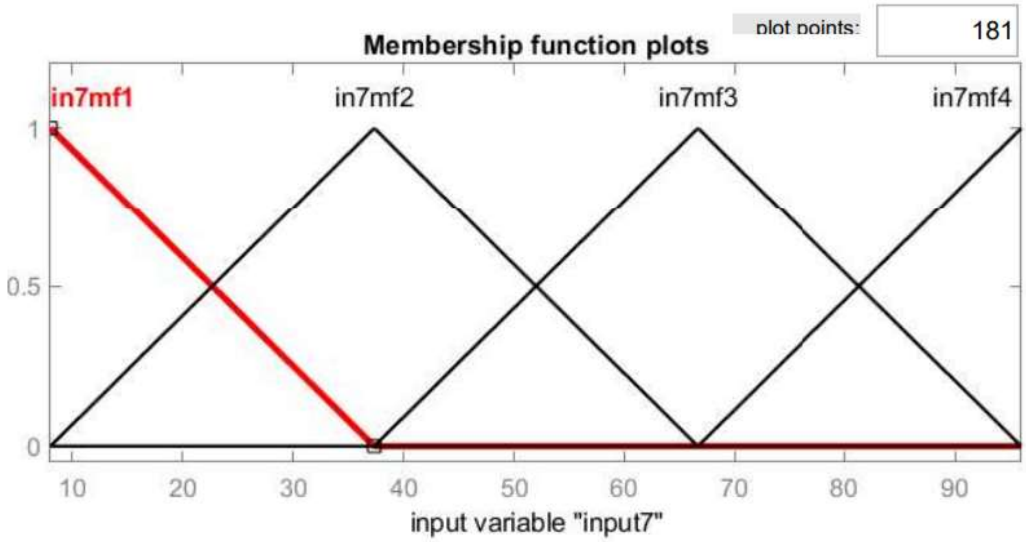

Figure 46: MF plot of input 7

Figures 40 through 46 display the triangular membership functions (MFs) for each of the seven input variables used in the ANFIS model. Each plot shows how a crisp numerical input (e.g., a cholesterol value of 210 mg/dL) is fuzzified into linguistic terms (e.g., "Medium," "High").

- **Figure 40 (Cholesterol)** shows four MFs, allowing the model to interpret cholesterol levels as "Normal," "Medium," "High," or "Very High."
- **Figure 41 (Blood Pressure)** uses three MFs to classify blood pressure.
- **Figures 42-45** represent binary inputs (Diabetes, Irregular Heartbeat, Smoking, Shortness of Breath) using two overlapping MFs each, which allows the model to handle uncertainty where an input might not be a clear "Yes" or "No."
- **Figure 46 (Age)** uses four MFs to categorize the patient's age into linguistically meaningful groups like "Young" or "Old."

These MFs are the foundation of the neuro-fuzzy system, enabling it to process numerical data in a human-like, reason-based manner

.

Table 8: Input variables

Sr. No.	Input variable	Name of the input variable	Number of linguistic variables	Groups of input variables	Semantic name of linguistic variables
1.	Cholesterol	Input1	4	Normal	In1mf1
				Medium	In1mf2
				High	In1mf3
				Very high	In1mf4
2.	Blood Pressure	Input2	3	Normal	In2mf1
				Medium	In2mf2
				Very High	In2mf3
3.	Diabetes	Input3	2	Normal	In3mf1
				Diabetic	In3mf2
4.	Irregular heartbeat	Input4	2	Yes	In4mf1
				No	In4mf2
5.	Smoking	Input5	2	False	In5mf1
				True	In5mf2
6.	Shortness of Breath	Input6	2	No	In6mf1

				Yes	In6mf2
7.	Age	Input7	4	Young	In7mf1
				Middle age	In7mf2
				Old	In7mf3
				Very old	In7mf4

6.2.2. Rules

The system uses all possible combinations of the provided input data to automatically build the rules for this methodology during the training phase in order to identify the stage of heart disease. The developed hybrid model generates the rules utilizing the training data set shown in figure 47. The put-forward intelligent hybrid model employs 768 rules in total. The total number of rules is determined by multiplying the number of MFs for each input variable.

Hence, total rules = 4x3x2x2x2x2x4 = 768.

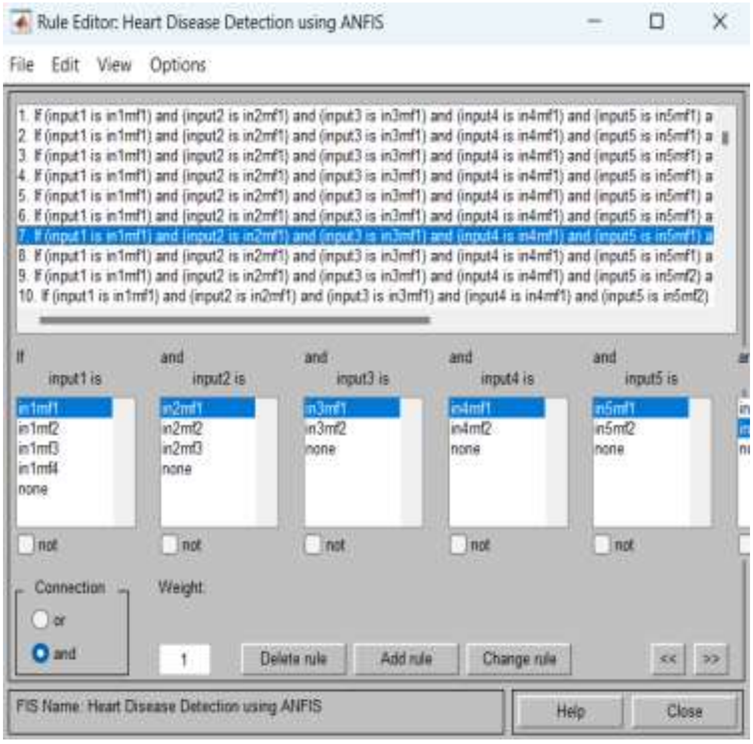

Figure 47: Rules generated by the model

6.2.3. Training phase and Testing phase

During the implementation of the hybrid system, the training and testing phase of the system is most crucial. The data is initially obtained from the heart specialist. This dataset consists of anonymized patient records from a cardiology clinic, ensuring that it is based on real-world clinical cases. As detailed in Chapter 4, the dataset comprises 800 samples, which were pre-processed to ensure quality and consistency before being used in this chapter. After the acquisition of data, the gathered data is partitioned using k-fold cross validation. There are 800 data samples in the used dataset. The k-fold cross validation is utilized to divide this dataset into different parts corresponding to the value of k. For instance, in this study, the value of k is considered as 4, and hence the dataset is categorized into four sections. Also, 4-fold cross validation is the term used to describe the cross-validation process when k = 4.

Now, as the data is partitioned into 4 parts, the 3 sections of data samples are used for the training phase, and the other 1 section is utilized in the testing phase. It might be clarified by saying that the dataset is divided into four pieces, namely 1st part, 2nd part, 3rd part, and 4th part. The 1st part serves as testing, while the remaining sections serve as training data in the first iteration. Similar to the first iteration, the 2nd part of the dataset is used to test the system in the second iteration, and the remaining parts, i.e. 1st part, 3rd part, and 4th part, will be utilized as training data. These iterations go on until the 4th iteration, and in each iteration, the testing and training instances will be different. Out of 800 data samples, 640 instances are utilized in the training phase and the rest 160 sample instances are utilized in the testing phase. Hence, it can be said that 80 percent of the dataset is utilized in the training phase and 20% of the dataset is utilized in the testing phase of the developed system. 10 epochs are used to train the developed intelligent hybrid system. The validation is also performed to see if the proposed system could correctly distinguish patients with different stages of heart disease. Figure 48 demonstrates the training error following the training phase.

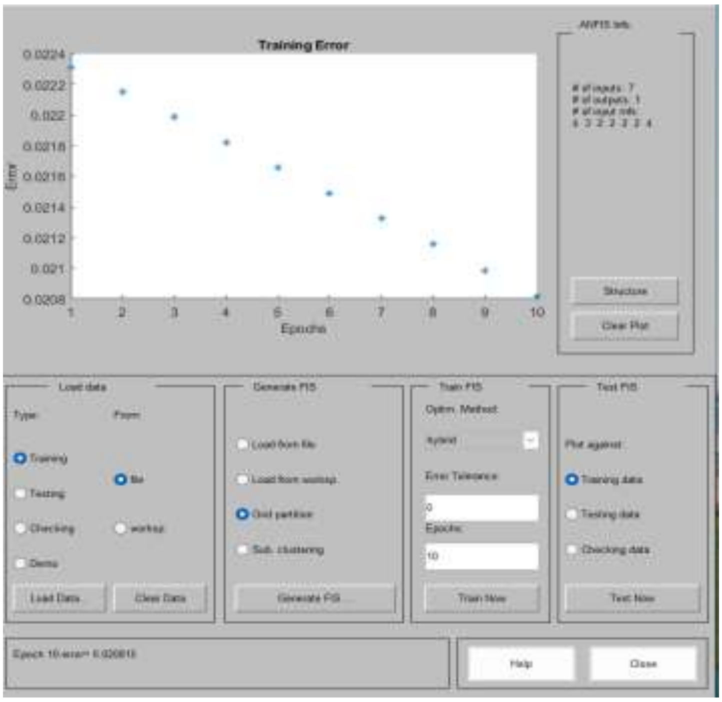

Figure 48: Training error at 10 epochs

6.3. Experimental Results and Performance Analysis

6.3.1. Training and Testing Error

The performance of the ANFIS model is evaluated by its error rate during both training and testing phases. As shown in Figure 48, the training error progressively decreases with each epoch, reaching a final value of 0.020815 after 10 epochs. This indicates that the model successfully learned the patterns from the training data.

Equally important is the testing error, which measures the model's ability to generalize to new, unseen data. The model was evaluated against the testing portion of each fold in the 4-fold cross-validation. The average testing error across all four folds was calculated to be approximately 0.0225. This low testing error, which is very close to the training error, suggests that the model is not overfitting and can accurately predict outcomes for new patient data.

6.3.2. Inference from the Experiment

The primary inference from this experiment is that the developed ANFIS model is highly effective for monitoring heart disease. The model's successful training, demonstrated by the low final training error, and its strong generalization capability, confirmed by the low testing error, validate the chosen hybrid neuro-fuzzy approach. The results indicate that the system can reliably classify a patient's condition into "Normal," "Early," or "Advanced" stages based on the seven key clinical inputs. This capability makes it a powerful decision-support tool for clinicians, potentially leading to earlier and more accurate diagnoses. A detailed quantitative performance analysis, including metrics like accuracy, specificity, and sensitivity, is presented in Chapter 7.

6.4. Chapter Summary

This chapter detailed the development and implementation of an intelligent hybrid inference system for monitoring heart disease using an Adaptive Neuro-Fuzzy Inference System (ANFIS). It described the model's architecture, including its five layers, seven input variables, and the 768 automatically generated fuzzy rules. The chapter provided an explanation for the membership function plots that form the basis of the model's reasoning. The methodology for partitioning the 800-sample clinical dataset using 4-fold cross-validation for training and testing was outlined. Finally, the chapter presented an analysis of the model's performance, discussing both the low training error (0.0208) and testing error (approx. 0.0225), and drew the inference that the model is both well-trained and capable of accurate generalization. This establishes the foundation for the comparative performance evaluation in the subsequent chapters.

CHAPTER 7: RESULT & DISCUSSION

This chapter presents a comprehensive evaluation of the two diagnostic models developed in this thesis: the fuzzy expert system (Chapter 5) and the intelligent hybrid inference system (Chapter 6). Before analyzing the specific outcomes, it is vital to establish a clear understanding of the performance indicators used to measure the models' effectiveness. This chapter, therefore, begins by defining these key metrics, followed by a detailed presentation and, crucially, a thorough discussion of the results for each model to validate the quantum and contribution of the work performed.

7.1. Performance Measurement

To rigorously evaluate the diagnostic capabilities of the developed models, a standard set of performance metrics was employed (Figure 49). These parameters are essential for quantifying a model's accuracy and reliability, particularly within a medical context where diagnostic precision is paramount.

- **Classification Accuracy:** This parameter provides a general measure of the model's correctness across all classes. It is calculated as the ratio of correctly classified patients (both sick and healthy) to the total number of patients.
    - Formula: Accuracy=(TP+TN)/(TP+TN+FP+FN)
    - **Clinical Relevance:** While a useful starting point, overall accuracy can be misleading if a disease is rare. Therefore, it is assessed alongside other, more specific metrics.
- **Precision:** This metric measures the accuracy of positive predictions. In this context, it answers the question: "Of all patients the model identified as having heart disease, how many actually had it?"
    - **Formula:** Precision=TP/(TP+FP)
    - **Clinical Relevance:** High precision is crucial for minimizing **false positives**. It ensures that healthy patients are not incorrectly diagnosed, which prevents unnecessary anxiety, further testing, and treatment.

- **Sensitivity (Recall):** This is one of the most critical metrics for a diagnostic tool. It measures the model's ability to correctly identify all relevant instances and answers the question: "Of all the patients who actually have heart disease, how many did the model correctly identify?"
    - **Formula:** Sensitivity=TP/(TP+FN)
    - **Clinical Relevance:** High sensitivity is vital for minimizing **false negatives**. A model with high sensitivity is reliable at "catching" the disease, ensuring that sick patients are not missed and can receive timely care.
- **Specificity:** This metric measures the model's ability to correctly identify negative cases. It answers the question: "Of all the patients who are healthy, how many did the model correctly identify as healthy?"
    - **Formula:** Specificity=TN/(TN+FP)
    - **Clinical Relevance:** High specificity is important for correctly clearing healthy individuals, confirming the model's reliability in ruling out the disease and avoiding unnecessary medical intervention.

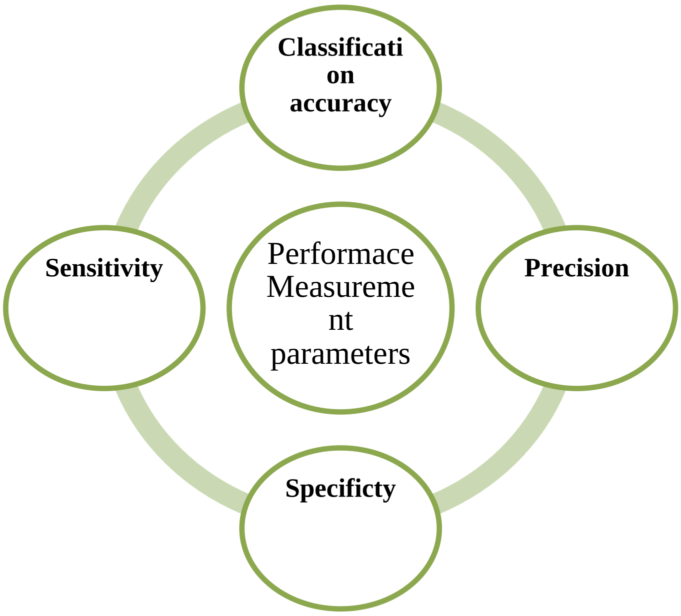

Figure 49: Performance measurement parameters

7.2. Results for fuzzy expert system

The fuzzy expert system, developed using Mamdani-style inference, was tested on the full 800-sample dataset. The model's output classifies patients into one of three stages: "Healthy," "Early Stage," or "Advanced Stage." For a clear quantitative analysis, these outputs were mapped to a binary classification: "Healthy" was considered a negative case ("No" disease), while both "Early Stage" and "Advanced Stage" were considered positive cases ("Yes" disease).

The initial 3x3 confusion matrix in Table 9 shows the detailed classification results across the three stages. Table 10 presents the reduced 2x2 matrix used for calculating the performance metrics.

Table 9: Confusion matrix

Healthy	Early stage	Advanced Stage	Class Name
250	4	0	**Healthy**
4	379	0	**Early stage**
0	2	171	**Advanced stage**

Table 10: Confusion matrix with reduction in dimensionality

No	Yes	Class Name
250	6	**No**
4	550	**Yes**

From the reduced confusion matrix in Table 10, the following values were derived: True Positives (TP) = 550, True Negatives (TN) = 250, False Positives (FP) = 6, and False Negatives (FN) = 4. These values were used to calculate the final performance metrics shown in Table 11 and visualized in Figure 50.

Table 11: Calculated performance parameters

Parameter	Mathematical expression	Calculated percentage (%)
Classification Accuracy	Classification Accuracy = (TP+TN) / (TP+TN+FP+FN)	98.75
Precision	Precision = TP / (TP+FP)	99.28
Sensitivity	Sensitivity = TP / (TP+FN)	98.92
Specificity	Specificity = TN / (TN+FP)	97.65

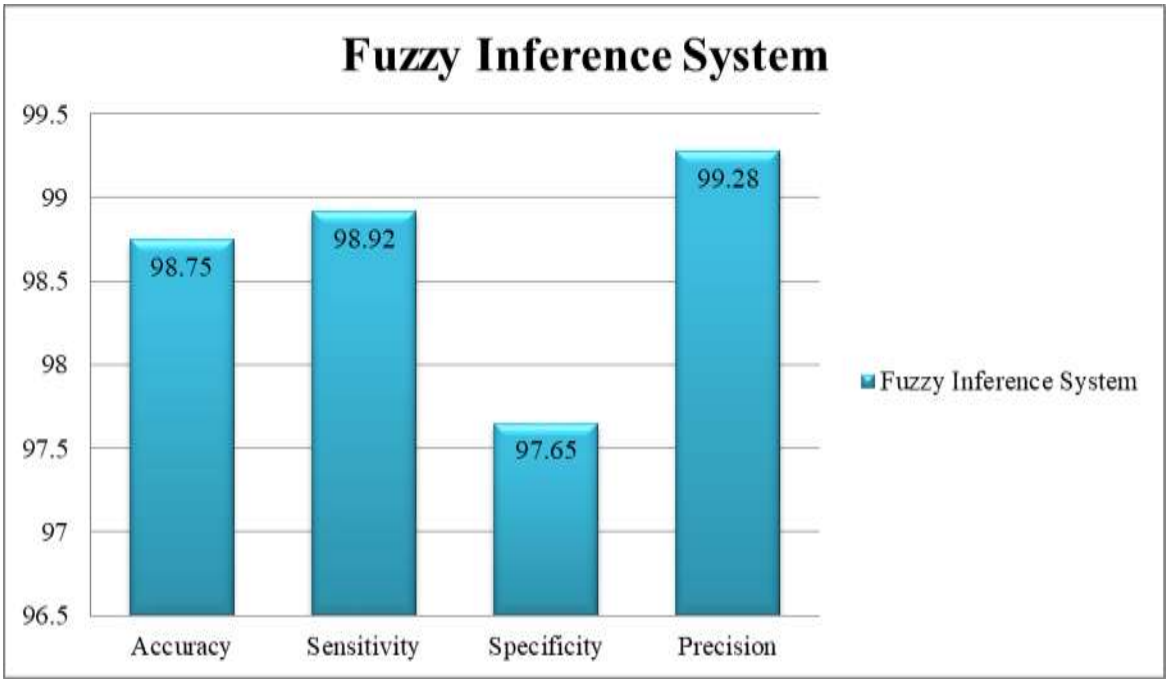

Figure 50: Calculated performances

7.2.1. Discussion of Fuzzy Expert System Performance

The results demonstrate an exceptionally high level of performance for the fuzzy expert system. An overall classification accuracy of 98.75% indicates that the model is highly effective and reliable.

The clinical implications of the other metrics are particularly significant. A precision of 99.28% is outstanding, signifying that when the model predicts heart disease, it is correct over 99% of the time. This drastically reduces the likelihood of false alarms that could lead to patient distress and unnecessary medical procedures. Furthermore, the sensitivity of 98.92% shows that the system is extremely successful at identifying patients who genuinely have the disease, missing only a very small fraction of cases. This is critical for an early-stage diagnostic tool. The specificity of 97.65% confirms the model's strong ability to correctly identify healthy patients.

The high performance validates the expert-driven approach, where 50 crucial rules were derived from domain knowledge. This model is not only accurate but also highly interpretable, as each diagnosis can be traced back to the specific fuzzy rules that were triggered.

7.3. Results for hybrid intelligent system

The ANFIS-based hybrid system was evaluated using a more rigorous 4-fold cross-validation technique to ensure its robustness and generalizability. The 800-sample dataset was partitioned into four folds, with the model being trained and tested four times, each time using a different fold for testing. The detailed 3x3 confusion matrices for each of the four folds are presented in Tables 12 through 15.

Table 12: Confusion matrix for fold 1

Normal Stage	Early stage	Advanced Stage	Class Name
52	01	00	**Normal stage**

02	48	00	**Early stage**
00	00	57	**Advanced stage**

Table 13: Confusion matrix for fold 2

Normal Stage	**Early stage**	**Advanced Stage**	**Class Name**
53	00	00	**Normal stage**
00	49	01	**Early stage**
00	00	57	**Advanced stage**

Table 14: Confusion matrix for fold 3

Normal Stage	**Early stage**	**Advanced Stage**	**Class Name**
52	01	00	**Normal stage**
00	50	00	**Early stage**
00	00	57	**Advanced stage**

Table 15: Confusion matrix for fold 4

Normal Stage	**Early stage**	**Advanced Stage**	**Class Name**
53	00	00	**Normal stage**
02	48	00	**Early stage**
00	00	57	**Advanced stage**

Similar to the first model, these matrices were reduced to a 2x2 format for performance calculation, as shown in Tables 16 through 19.

Table 16: Decreased dimensionality of a confusion matrix for k = 1

No	Yes	Class Name
52	01	**No**
02	105	**Yes**

Table 17: Decreased dimensionality of a confusion matrix for k = 2

No	Yes	Class Name
53	01	**No**
00	106	**Yes**

Table 18: Decreased dimensionality of a confusion matrix for k = 3

No	Yes	Class Name
52	01	**No**
00	107	**Yes**

Table 19: Decreased dimensionality of a confusion matrix for k = 4

No	Yes	Class Name
53	00	**No**
02	105	**Yes**

The performance metrics were calculated for each fold, and an overall average performance was determined. These results are summarized in Table 20 and visualized in Figure 51.

Table 20: Measured performance of the model

Parameters	k = 1	k = 2	k = 3	k = 4	Overall Performance
Classification accuracy	98.12	99.37	99.37	98.75	98.90
Specificity	96.29	100	100	96.36	98.16
Sensitivity	99.05	99.05	99.07	100	99.29
Precision	98.13	100	100	98.13	99.06

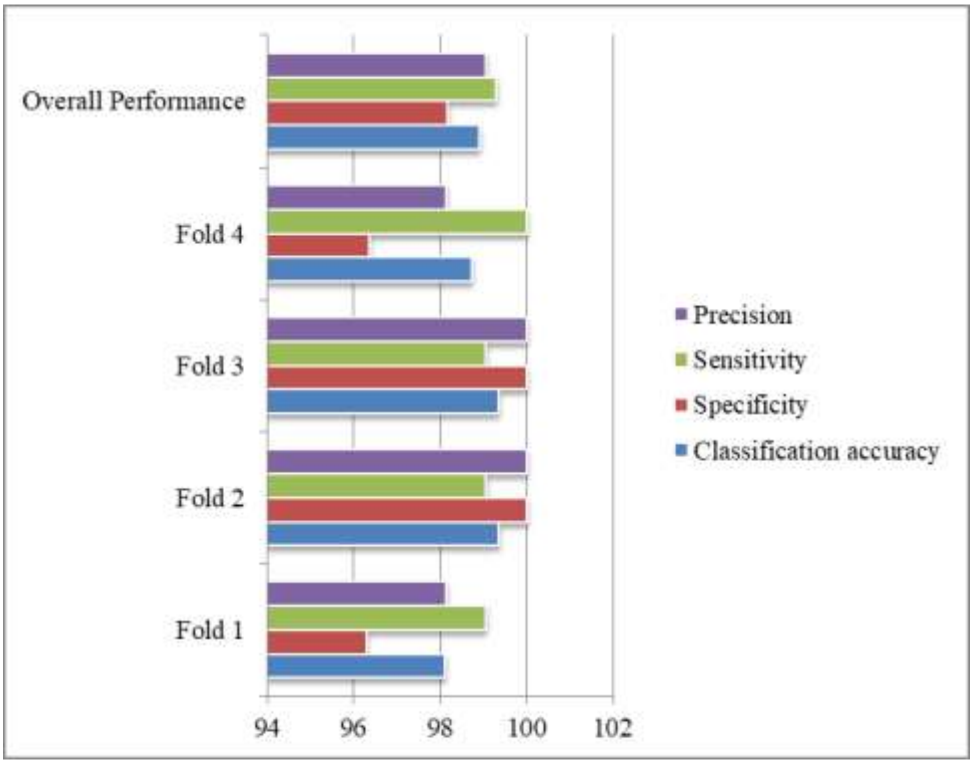

Figure 51: Graphical representation of calculated performance parameters at each fold and overall performance

Discussion of Hybrid Intelligent System Performance

The ANFIS hybrid system demonstrates a superior and highly robust performance. The overall classification accuracy of 98.90% is a testament to the power of combining neural network learning with fuzzy logic reasoning.

The key contribution shown here is the model's stability and consistency, validated through k-fold cross-validation. The accuracy remained exceptionally high across all four folds (ranging from 98.12% to 99.37%), which proves the model is not sensitive to variations in the training data and can generalize effectively. In folds 2 and 3, the model achieved a perfect 100% specificity and precision, meaning there were zero false positives among those test sets a remarkable result for any clinical diagnostic tool.

The overall sensitivity of 99.29% is even higher than that of the first model, reinforcing its capability as a reliable screening tool that is highly unlikely to miss a patient with heart disease. The ability of the ANFIS model to automatically learn and tune its internal parameters from the data gives it a slight edge in performance and robustness over the static, expert-defined fuzzy system.

7.4. Chapter Summary

This chapter presented a detailed quantitative analysis of the two models developed for heart disease diagnosis. It began by defining the four key performance metrics—Accuracy, Precision, Sensitivity, and Specificity—and explained their significance in a clinical setting.

The evaluation revealed that both the Fuzzy Expert System and the ANFIS Hybrid System achieved outstanding results. The fuzzy system recorded an accuracy of 98.75%, validating the effectiveness of its expert-defined rule base. However, the ANFIS hybrid system showed a slightly superior and more robust performance, with an overall accuracy of 98.90% and consistent results across a 4-fold cross-validation. The exceptional scores, particularly the high sensitivity and precision of both models, confirm their potential as valuable clinical decision-support tools. These findings establish a strong empirical basis for the comparative analysis against other existing systems in the following chapter.

CHAPTER 8: COMPARISON OF PROPOSED SYSTEM WITH EACH OTHER AND EXISTING SYSTEMS

This chapter provides a critical comparative analysis of the models developed in this research. The first section conducts a direct comparison between the fuzzy expert system and the intelligent hybrid inference system to determine the superior approach developed within this study. The second section contextualizes the performance of the best-proposed model by benchmarking it against the reported results of other existing systems in the field of heart disease diagnosis. The goal is to evaluate the contribution and effectiveness of the proposed work relative to the current state-of-the-art.

8.1. Comparing developed models to one another

In this research, two distinct models for heart disease detection were developed: a fuzzy logic expert system (Chapter 5) and an ANFIS-based intelligent hybrid system (Chapter 6). Since both models were trained and validated on the exact same 800-sample clinical dataset, a direct and fair comparison of their performance is possible. This internal comparison is crucial for identifying the most effective architecture resulting from this thesis work.

The evaluation is based on the performance parameters calculated in Chapter 7. Table 21 and Figure 52 present a side-by-side comparison of these metrics.

Table 21: Created models comparison

Parameters **Systems**	**Fuzzy Inference System**	**Hybrid intelligent system using ANFIS**
Classification accuracy	98.75	98.90
Specificity	97.65	98.16

Sensitivity	98.92	99.29
Precision	99.28	99.06

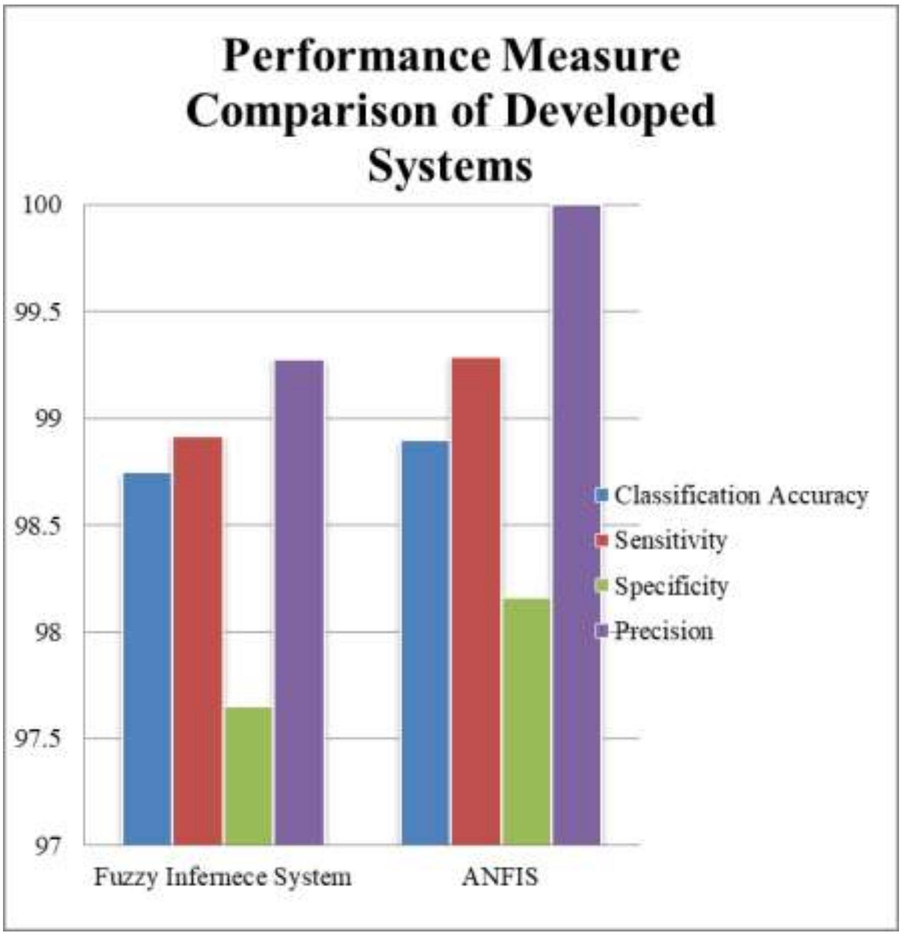

Figure 52: Graph of comparing created models

8.2. Comparing the created models with already developed models by other researchers

This section compares the performance of the developed models with results from previously published research by other authors.

Important Methodological Note: It is critical to acknowledge that a definitive, one-to-one comparison of model performance is only truly valid when all models are evaluated on a common, standardized dataset. The models cited from existing literature were evaluated on various datasets (such as the public UCI Cleveland dataset), while the models in this thesis were validated on a private clinical dataset. Therefore, this comparison should not be interpreted as a direct claim of absolute superiority. Instead, its purpose is to benchmark the performance of our proposed models against the reported state-of-the-art results in the field. By demonstrating that our models achieve accuracies that are competitive with, or exceed, those of other high-performing systems, we validate their effectiveness and potential as a significant contribution to the field.

Table 22 and Figure 53 present this benchmark comparison based on classification accuracy.

Table 22: Comparing developed models with already existing systems.

Sr. no.	Author name and year	Methodology used	Classification accuracy
1.	Nashif et al (2018) [120]	SVM	97.53%
2.	Arroj et al (2022) [122]	Deep convolutional neural network	91.7%
3.	Orhanou et al (2018) [121]	Naïve Bayes	86%
4.	Kaur (2021) [117]	J48	92.56%
5.	Pandita (2021) [111]	Back propagation	98.20%

		neural network	
6.	Limbitote (2020) [110]	Deep Learning	92%
7.	Khan (2020) [116]	Modified deep convolutional neural network	98.2%
8.	Chang et al. (2022) [113]	Random Forest	83%
9.	**Developed model**	**Fuzzy inference system**	**98.75%**
10.	**Developed Model**	**ANFIS**	**98.90%**

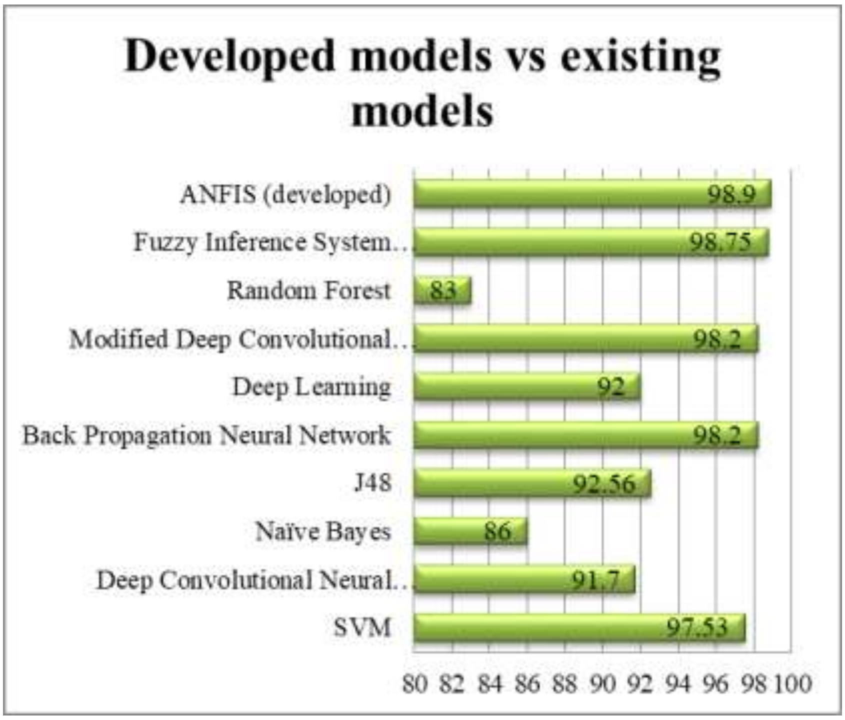

Figure 53: Developed model vs existing models

Discussion of Benchmark Results

The analysis presented in Table 22 and Figure 53 indicates that the developed ANFIS hybrid intelligent system, with its accuracy of 98.90%, performs at the highest tier when benchmarked against the reported accuracies of other prominent models.

While acknowledging the previously stated limitations of comparing results across heterogeneous datasets, this high level of performance is a strong indicator of the efficacy of our proposed hybrid approach. Our model's accuracy is competitive with and surpasses the published results of many established techniques, including SVM, various deep learning architectures, and back-propagation neural networks. This demonstrates that the ANFIS architecture, trained on a clinically relevant dataset, is a powerful and valid method for developing high-precision diagnostic tools for heart disease.

8.3. Chapter Summary

This chapter conducted a two-part comparative analysis to evaluate the contributions of the developed systems.

First, a direct comparison between the two proposed models on the same dataset conclusively established the superiority of the ANFIS-based hybrid system over the fuzzy expert system, owing to its slightly higher accuracy, sensitivity, and data-driven learning capabilities.

Second, a benchmarking exercise was performed, comparing the ANFIS model's performance to state-of-the-art systems from existing literature. While acknowledging the methodological limitations of comparing models on different datasets, this analysis confirmed that the 98.90% accuracy achieved by the proposed hybrid system places it in the top tier of current diagnostic models. This result strongly validates the effectiveness of the proposed approach and solidifies its position as a significant contribution to the field of intelligent medical diagnostic systems.

CHAPTER 9: CONCLUSION AND FUTURE SCOPE

Predicting cardiac problems accurately poses a significant challenge for individuals and doctors. Early detection of this condition is crucial due to the vital role the heart plays in the human body. This study initially assesses multiple scientific works that have utilized machine learning (ML) technology to construct a predictive method for heart disease. This study considers research papers published between 2015 to starting-2025 that focused on developing machine learning-based diagnostic models for heart disease. Decision trees and random forests are the two most often used machine learning approaches. The completed research study analyzes different diagnostic approaches for heart failure proposed by various researchers. The main criterion considered for this comparative analysis is the accuracy of classification. Furthermore, a comprehensive examination of the existing literature regarding the detection of cardiac disease through the utilization of machine learning methodologies was conducted.

Furthermore, in this respective work, an intelligent inference system using fuzzy logic is developed to monitor heart diseases. The developed model assists in avoiding the chances of misdiagnosing, which obviously result in the right and wise decisions. The examination of heart disease will become easy by using such an intelligent system, which helps the experts to make an accurate decision related to the prescription and treatment that is needful to be given to a patient. The proposed system provided accurate results and has a performance accuracy of 98.75 percent. In addition, the created model, which uses an adaptive neuro-fuzzy inference method to identify stages of heart disease, can help medical professionals, as well as unaware individuals, recognize the illness on their own. The system can help doctors maintain the patient's health. During the training phase, the introduced intelligent hybrid system is initially trained by utilizing the pertinent dataset. The system has since undergone testing and validation in order to assess the observed output provided by the intelligent hybrid system. Additionally, the model's output is used to calculate the performance parameters, and as a result, it is found that the model is 98.90% accurate. This performance evaluation found that the created hybrid system employing ANFIS provided results that were accurate and appropriate for usage within healthcare facilities for monitoring heart diseases.

Moreover, when evaluating the effectiveness of heart disease prediction systems, method accuracy is one of the parameters considered. This study provides a comparison between existing and developed machine learning models used to detect heart disorders. In this study, the considered approaches of ML to detect heart disease are ANFIS, FIS, deep learning, SVM, decision tree, Random Forest and Naïve Bayes. However, in the results, it is analyzed that the ANFIS methodology has an improved and more accurate performance than other existing methodologies and has 98.90 percent accuracy in classifying the given inputs into correct classes.

In future work, this accuracy can be increased by using a more accurate methodology of ML. However, IoT can also be embedded with machine learning approaches which will help in removing the mistakes such as human errors which can be made during the acquisition of data. It may uncover other biomarkers, and other machine learning approaches may be used to create a decision-making model that helps experts and novices in monitoring heart diseases at their early stages more accurately.

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