A NOVEL MACHINE LEARNING BASED REAL-TIME VITAL SIGN MONITORING SYSTEM

Thesis Submitted for the Award of the Degree of

DOCTOR OF PHILOSOPHY

in

Department of Computer Science and Engineering

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Transforming Education Transforming India

LOVELY PROFESSIONAL UNIVERSITY, PUNJAB

2025

<u>**DECLARATION**</u>

I, hereby declared that the presented work in the thesis entitled "**A Novel Machine Learning Based Real-time Vital Sign Monitoring System**" in fulfilment of degree of **Doctor of Philosophy (Ph. D.)** is outcome of research work carried out by me under the supervision of **Dr. Gurpreet 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 investigator. 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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<u>CERTIFICATE</u>

This is to certify that the work reported in the Ph. D. thesis entitled "**A Novel Machine Learning Based Real-time Vital Sign Monitoring System**" submitted in fulfillment of the requirement for the award of degree of **Doctor of Philosophy (Ph.D.)** in the **Department of Computer Science and Engineering**, is a research work carried out by **Amit Sundas, 42100013**, is bonafide record of his original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.

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ABSTRACT

Significant economic and social concerns are raised by the global proliferation of chronic and lifestyle-related maladies. Therefore, this study looks into healthcare tracking systems in more depth in order to solve these issues. Deep learning and cloud-based analytics are used in the Smart Patient Monitoring and Recommendation (SPMR) platform.

Reviewing existing healthcare monitoring systems is the first step in the investigation, which concludes with the creation of the SPMR framework. This system enables ongoing monitoring and predictive insights into a patient's current health status by using data from contextual behaviors and vital signs collected by Ambient Assisted Living devices.

Categorical Cross Entropy (CCE) optimization is used by SPMR's predictive deep learning component to estimate real-world health outcomes from imbalanced datasets collected from instances of chronic blood pressure disorder. By eliminating the need to replicate Machine Learning (ML) models and associated processes in local settings, SPMR's ability to provide real-time preventative measures and treatments is unaffected by an Internet or cloud connection, improving operational efficiency.

A comparative analysis of our proposed SPMR model with comparable models reveals its substantial efficacy, with accuracy enhancements ranging from 8 to 18 percent. In addition, the emergency class F-score and the aggregate F-score demonstrate substantial improvements of 17% and 36%, respectively. These results underscore the critical significance of SPMR, particularly during periods of crisis, emphasizing its relevance in healthcare monitoring systems.

Additionally, our research addresses the critical aspect of security in Smart Healthcare Systems (SHSs) through the introduction of HealthGuard, an innovative security architecture. HealthGuard employs machine learning algorithms to detect potentially detrimental behaviors performed by users inside SHSs, monitoring vitals of connected devices and distinguishing normal from abnormal activity. Four different machine learning-based detection techniques are used in the architecture (Random Forest, Artificial Neural Network, Decision Tree, and k-Nearest Neighbor), demonstrating a 91% success rate and an F1-score of 90% in defending against various attacks.

Overall, the integration of DL, cloud-based analytics, IoT, and ubiquitous computing in SPMR and the implementation of HealthGuard represent a paradigm shift in real-time vital sign

monitoring and healthcare security. These developments indicate that they will offer considerable enhancements in patient safety, healthcare administration, and decision-making in response to the growing security threats and challenges.

ACKNOWLEDGMENT

First and foremost, I express my profound gratitude to Almighty for bestowing upon me the strength, patience, and wisdom necessary to achieve the objectives of my PhD work. The grace, love, and support provided by the Almighty have been fundamental to this accomplishment.

I am deeply indebted to my supervisor, Dr. Gurpreet Singh, and my co-supervisor, Dr. Sumit Badotra, for their unwavering guidance and insightful feedback. Their expertise, dedication, and encouragement have been instrumental in the successful completion of this research. Their constructive criticism and persistent support have greatly enriched my academic journey.

I wish to extend my deepest gratitude to my family. I am at a loss for words to adequately thank my father, Mr. Surjya Sundas, and my mother, Mrs. Reena Sundas, for their exceptional support, provided in all forms and at times when I needed it most. Their sacrifices, love, and unending faith in me have been the cornerstone of my perseverance and success. Their constant support and encouragement have been a source of immense strength and motivation throughout this arduous journey.

I sincerely thank my siblings and family for their constant support, encouragement, and belief in me. Your unwavering faith has been a major driving force behind my achievements.

I am also grateful to my friends and colleagues for their camaraderie, intellectual stimulation, and shared laughter, making this journey enjoyable and less solitary.

To all of you, I offer my heartfelt thanks. Your contributions and support have been invaluable, and this achievement would not have been possible without your collective encouragement and guidance.

(Amit Sundas)

ABBREVIATIONS

AAL	Ambient Assisted Living
AUROC	Area Under the Receiver Operating Characteristic Curve
AI	Artificial Intelligence
ANNs	Artificial Neural Networks
ASD	Autism Spectrum Disorder
bpm	Beats Per Minute
BP	Blood Pressure
BWSN	Body Wireless Sensor Network
CCE	Categorical Cross Entropy
CDPU	Central Data Processing Unit
CHF	Chronic Heart Failure
CKD	Chronic Kidney Disease
COPD	Chronic Obstructive Pulmonary Disease
CMM	Cloud Monitoring Module
CPM	Cloud Predictive Model
CF	Conditional Forest
CCE	Context Of Optimization Could
CA	Conversation Analysis
CNNs	Convolutional Neural Networks

Core BT	Core Body Temperature
DT	Decision Tree
DL	Deep Learning
EWS	Early Warning Systems
EC2	Elastic Compute Cloud
Enet	Elastic Net Regression
ECG	Electrocardiogram
EEG	Electroencephalography
EMG	Electromyography
EDI	Electronic Data Interchange
EHRs	Electronic Health Records
GSR	Galvanic Skin Response
GA	Genetic Algorithm
GPS	Global Positioning System
GCP	Google Cloud Platform
HR	Heart Rate
HRV	Heart Rate Variability
HD	Hospital Department
ICDs	Implantable Cardiac Defibrillators
IMDs	Implantable Medical Devices

ICUs	Intensive Care Unit
IDC	International Data Corporation
IoMT	Internet Of Medical Things
IoT	Internet Of Things
IoTTA	IoT Tiered Architecture
KNN	K-Nearest Neighbors
LASSO	Least Absolute Shrinkage and Selection Operator
LPM	Lifestyle Prediction Mechanism
LIP	Local Intelligent Processing
LPM	Local Predictive Model
LPSU	Local Processing and Storage Facility Unit
ML	Machine Learning
MLA	Machine Learning Algorithms
MRI	Magnetic Resonance Imaging
MATLAB	Matrix Laboratory
MC	Medical Cloud
MIMIC	Medical Information Mart for Intensive Care
MEWS	Modified Early Warning Score
NEWS	National Early Warning Score
NLP	Natural Language Processing

NB	Nave Bayes
NN	Neutral Network
OPDB	Online Patent Database
SpO2	Oxygen Saturation
P2P	Peer-To-Peer
PCA	Principal Component Analysis
RBFs	Radial Basis Functions
RFID	Radio Frequency Identification
RF	Random Forest
RNNs	Recurrent Neural Networks
RR	Respiratory Rate
SOA	Service-Oriented Architecture
SNNs	Simulated Neural Networks
SHSs	Smart Healthcare Systems
SPMR	Smart Patient Monitoring and Recommendation
SGD	Stochastic Gradient Descent
SVM	Support Vector Machine
SHARP	Sustainable, Holistic, Adaptive, Real-Time, And Precise
WBAN	Wireless Body Area Network
WSN	Wireless Sensor Network

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Chapter 1: Introduction

Overview

In this chapter, an augmented real-time monitoring system based on machine learning methods is implemented and the traditional systems for monitoring vital signs are examined in detail. It investigates the vital signs monitoring, the specific features and type of the vital signs which are monitored, standard monitoring devices and its limitation. This chapter also explores applications of machine learning within healthcare technology and its potential to enhance real time monitoring through anomalies detection, predictive analysis and tailoring care for individual patients. It also clarifies the objectives and main features of the proposed system with an emphasis on its innovative aspect for the betterment of the healthcare monitoring systems.

1.1. Background and Motivation

1.1.1. Vital sign monitoring methods

Traditional vital sign monitoring techniques have been widely used in healthcare for a long time to provide important information about a patient's physiological state. Most of these procedures involve the examination and monitoring of several vital signs, which are important indicators of general health and well-being [1]. The most commonly used conventional vital signs include:

- **Heart Rate (HR)**: A very important indication of cardiovascular health, the heart rate measures the beats per minute (bpm), which is an important statistical measure. It can usually be evaluated by means of electrocardiograms or ECGs, by pulse oximeters, or by manual pulse location palpation [2].
- **Blood Pressure (BP)**: The blood pressure represents forces exerted by blood when flowing through arteries and impacting their walls. The measurement for blood pressure consists of systolic and diastolic pressures during and between the heartbeats, in millimeters of mercury: mmHg. Such blood pressure can be found using sphygmomanometer and any other related equipment used in taking blood pressure readings.
- **Respiratory Rate (RR)**: Also known as the RR, the number of breaths taken per minute indicates how well the lungs are functioning and the respiratory system is operating. Breath rates are measured from chest movements or special apparatuses.

- **Temperature**: The amount of heat present in the body, also called body temperature, is essential for determining the metabolic rate and the health status of the individual. The measurement is done by using thermometers which are in most instances placed in the mouth, rectum or armpit [4-5].
- **Oxygen Saturation (SpO2)**: This value is expressed as a percentage which is derived by determining the fraction of oxygen saturation of hemoglobin in the blood. To monitor this parameter, which is very important in evaluating a patient's breathing, pulse oximeters are used, which are non-invasive devices.

Electrocardiograms, thermometers, blood pressure monitors, and even thermometers are among the various devices used to monitor vital signs according to the standard procedures. These primary indicators are collected by a nurse or a doctor and evaluated during periodic testing, clinical visits or emergency consultations. Although these measures succeed to provide important data, they do impose some limitations [6].

1.1.2. Limitations of Traditional Vital Sign Monitoring

Blood pressure, heart rate and temperature continue to be checked with devices inside hospitals. On the other hand such devices may create concerns and could negatively impact the safety of patients.

- **Intermittent Monitoring**: At each round, vital signs are measured, but the patient's health can change without warning. For example, a post-visit drop in oxygen saturation could be found on the next check, even though it happened important hours away [7-8].
- **Manual Analysis and Recording**: Staff and nurses gather data manually and handle its analysis later, as technology improves. Doing things manually may mean waiting longer and requiring more steps to keep control of the process. In one case, a UK hospital was unable to treat patients in septic shock because their vital signs were recorded on paper which took too much time [9].
- **Subjectivity**: Because of personal biases, one data set may be analyzed differently by different individuals. How people understand data completely depends on them. To cite an example, one of the nurses in a U.S. case was less experienced and, after seeing combination symptoms confused them for early heart distress [10].

- **Restricted Data Examination**: Because old systems do not represent a patient's progress step by step, it's hard to notice small ongoing changes. No notifications were available at some legacy ICUs for slower oxygen drop cycles at night which limited staff from acting on such situations [11].
- **Patient Adherence:** Participating in steps such as blood pressure or temperature checks requires patients to be still. This situation probably causes difficulty for infants, those who are unconscious or people with mental health disorders [12].
- **Demanding on Resources**: Standard monitoring involves a doctor, along with the use of cuff monitors and thermometers. During busy hospital times or emergencies like COVID-19, having enough staff was a big problem for the health system [13].
- **Scalability and Accessibility**: It can be very hard to observe and monitor lots of patients in remote settings at the same time. In India, some small clinics face challenges providing monitoring of patients who need emergency care because they often lack both staff and necessary devices [14].

Case Study: Recently, a patient who had just gone through surgery in a New York hospital had a sudden crash because abnormal vital signs were caught but not identified in time. The information from the vital signs was paper recorded, but there wasn't a quick check on it. The patient would have survived if an alert had been sent right away [13].

Today's devices watch for changes in a patient's vital signs, inform caregivers right away and may use Artificial Intelligence to spot potential issues early. Improving patient care at this point is both helpful and can save lives [14].

Problems with Technology:

- **Categories of Concern Data Privacy**: The use of wearables to collect and send health information creates major concerns about privacy. There are credible concerns about where the data resides, who can work with it and how it is protected.
- **Old Systems Compatibility:** Much hospital software is still developed by a single vendor and used throughout the organization. Using the latest monitoring platforms and AI with old systems is often very expensive, requires a lot of time and is not simple.

- **Resistance Acceptance:** Just like with any new innovation, healthcare staff have to be given the proper training. There are those who oppose new innovations or settle for approaches they have used for a while.

Even with some obstacles, bringing in smart technology to monitor patients in real time makes patient care quicker, safer and more precise, mainly when a patient's condition is urgent [5-6].

1.1.3. Advancements with Real-Time Monitoring and Machine Learning

Monitoring vital signs in traditional means has, replacing the ever medium of monitoring paitients and providing medical attention to them. The procedure involves a periodic assessment of critical parameters of the body such as pulse, temperature, respiration rate and blood pressure, so as to certify the physiological condition of a patient. Unlike the usual methods of monitoring patients' status, it still requires the collection of data which is quite sporadic, dependent on people and also makes it difficult for sustained monitoring to be done. [15].

However, the use of machine learning algorithms and real time monitoring systems seamlessly resolve these issues by allowing for unprecedented active monitoring of the vitals of a patient in a seamless manner. With real time monitoring devices, it becomes possible to stream multiple data points about a patient's physiologic condition as a single bulk. [16-17]. This data can then be analyzed through machine learning algorithms where patterns, trends and abnormalities that show deviations in the patients' condition can be detected in real time.

The integration of machine learning algorithms in real time surveillance systems has no doubt transformed the way healthcare facilities used to monitor and assess vital signs and their response to them [18]. The following mechanisms highlight how machine learning improves on real-time monitoring:

- **Continuous Data Acquisition**: Surveillance systems enhanced by machine learning are equipped to consistently gather essential vital sign information from peripheral devices, Internet of Things sensors, and electronic health records. This guarantees an ongoing and up-to-date stream of information [19].

- **Automated Analysis and Pattern Recognition**: Machine learning algorithms can independently analyze extensive amounts of vital sign data to identify anomalies, trends, and patterns that could signal health risks or shifts in a patient's condition. [20].
- **Predictive Analytics**: Machine learning algorithms possess the ability to anticipate future health outcomes, predict negative events, and provide early warning alerts to healthcare professionals by leveraging historical data and predictive modeling [21].
- **Tailored Insights**: By tailoring insights according to patient profiles, medical histories, and risk factors, ML algorithms can aid in crafting customized interventions and treatment strategies. [22].
- **Scalability and Efficiency**: Monitoring systems powered by machine learning can adeptly handle large datasets, support remote monitoring initiatives, and enhance the distribution of healthcare resources [23].
- **Feedback Loop and Learning**: Machine learning algorithms possess the capacity to gain knowledge and refine their predictive abilities as time progresses, thus creating a cycle that enhances the accuracy and relevance of monitoring insights.

1.2. Real-Time Monitoring Systems Enhanced by Machine Learning

1.2.1. Continuous Data Collection and Analysis

The real-time monitoring system employs a network of connected devices and sensors to continuously capture vital signs. This network essentially aims to chart a variety of physiological metrics like heart rate, blood pressure, respiratory rate, temperature, and oxygen saturation. The collected data is then sent for further analysis to the main database or the cloud and includes a timestamp [24-25].

1.2.2. Machine Learning Algorithms for Pattern Recognition

New health monitoring systems use machine learning to spot particular patterns and adjustments in your health data. They check through data that people cannot process and warn medical staff when needed. There are three main groups into which machine learning techniques in such systems are classified:

- **Supervised Learning:** In Supervised Learning, the system relies on provided data along with its correct answers to learn. Feeding knowledge this way is not much different than teaching someone with flashcards and giving answers. For example, a supervised learning model is taught about heart issues by exposing it to data on regular and irregular ECG patterns [26].

- **Unsupervised Learning:** The system performs its analysis without being given directions regarding the study's parameters. It sorts like records and points out any that stray a lot from the others as unusual. This approach could detect exact changes in a patient's vital signs that might hint at risk to their health [27-28].
- **Deep Learning:** Deep learning is included under the more general field known as deep learning. Deep learning is considered a complex branch of artificial intelligence (or machine learning) involving a lot of detailed data. It links new data without being shown steps and behaves like human reasoning for data that varies with time such as heart rate and blood pressure. RNNs and CNNs are the main neural network models for analyzing time data series. They are capable of finding patterns and links that might affect how a patient's health is changing [29].

1.2.3. Adaptive and Predictive Insights

An essential benefit of incorporating machine learning into real-time surveillance systems is the production of insightful observations that are both predictive and adaptive:

- **Adaptive Insights:** Adaptation of machine learning models to fluctuating physiological conditions and individual patient variations is possible. By modifying alert thresholds in accordance with a patient's baseline vital sign parameters, for instance, an adaptive monitoring system can decrease false alarms and increase the system's precision [30].
- **Predictive Insights:** Machine learning models have the capability to predict trends and prospective health outcomes through the analysis of both historical data and real-time inputs. By analyzing current vital sign patterns and medical history, predictive analytics can, for instance, assess which patients are at danger of declining or forecast the probability of particular medical events [31].

1.2.4. Data Fusion

Information from wearable gadgets, EHRs and x-ray images can all be collected by real-time monitoring systems. Using machine learning and data fusion, these systems make it possible to process and review this data to fully understand a patient's health [32].

1.2.5. Continuous Model Refinement

In order to function as real-time monitoring systems, machine learning models are consistently updated and refined in response to feedback and new data. The implementation of this iterative procedure guarantees that the models maintain their precision and efficacy in anomaly detection, outcome prediction, and the provision of practical insights for healthcare providers [25].

1.3. Healthcare Machine Learning: Uses and Possibilities

ML (machine learning) is a concept that must be defined prior to discussing its application in healthcare. ML is concerned with developing statistical models and techniques that enable computers to make forecasts or choices based on data, which is a branch of AI. ML Systems execute better over time without being explicitly programmed, in contrast to traditional programming which requires explicit instructions. These algorithms acquire knowledge from data patterns and experiences [26].

1.3.1. Machine Learning Algorithms

Using ML, a computer can decide on a task by learning from data, instead of requiring software for each single job. They make it possible for computers to pick out data patterns and analyze them by themselves. Fig. 1 displays the main classifications of algorithms into four types:

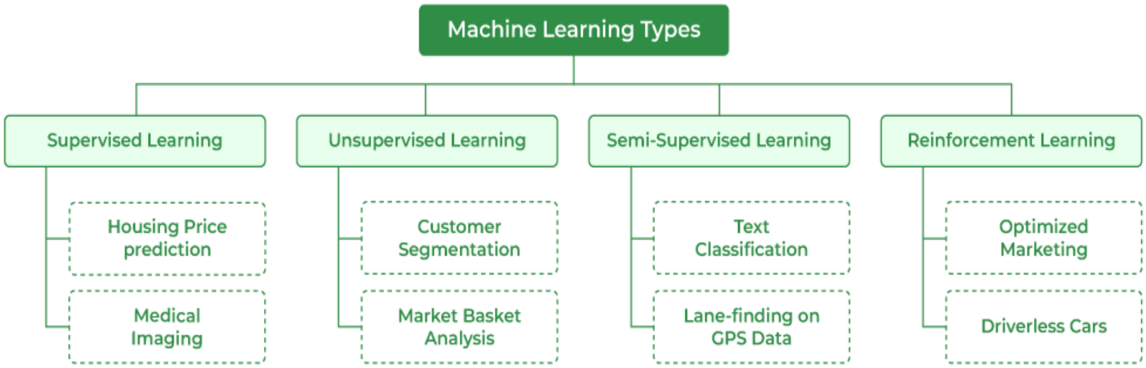


Figure 1. Different Machine Learning Forms.

i. **Supervised Learning:** If we use supervised learning, we feed the computer data with predetermined answers. It is a little like handing a student examples of problems and the solutions together.

In order for a computer to predict house prices, we give it the home's size, number of rooms and garden information alongside the actual house prices. When the computer has seen enough new and old house prices, it starts making accurate predictions for new homes [33].

- **Forecasting, regression, and classification are all included under the general heading of supervised learning.:**

a. **Classification:** During classification, a computer uses previous examples (from the training dataset) to help it make predictions or choices. The main thing is to place data into groups such as telling an email is spam or picking out the gender of someone's voice [33].

- **Types of Classification Algorithms:**
  - *Naive Bayes classifier:* This classifier which works with probability, assumes that every feature is unrelated to every other feature and uses Bayes' theorem. It's a simple and effective approach for labelling text such as organizing emails or reviewing how people feel about something [34].
  - *Decision Trees:* Decision trees are adaptable algorithms that generate a tree-like structure of decisions by recursively dividing the data along its features. An internal node corresponds to a feature, an outer branch to a decision, and a leaf

node to a class label or result. They are user-friendly, intuitive, and capable of processing categorical and numeric data [34].

- *Logistic Regression:* As the name implies, this classification technique is used for binary classification problems. The possibility of a binary result is represented by a logistic function (e.g., true/false or yes/no). Its efficacy for linearly separable data, simplicity, and interpretability contribute to its widespread application [30].
- *K-Nearest Neighbors (KNN):* K-Nearest Neighbors (KNN) is a straightforward technique using which the computer examines the closest data points to determine the group a new sample belongs to. It lends itself well to bringing together similar items, but sometimes it struggles with data that is both messy and complex [32].
- *Support Vector Machine (SVM):* Support Vector Machine (SVM) is a method designed to sort out data points. It does so by figuring out the best spot or feature to separate one group from another. SVM uses kernels which are special tools, to ensure it can handle simple as well as challenging data and draw lines that match what is required [33].
- *Random Forest Classification:* This classification method involves constructing different decision trees and practically combine their results to boost consistency. For challenging datasets, it is particularly successful, stays free from usual obstacles like overfitting and guides you to focus on the factors making the decision [34].

b. **Regression:** The purpose of using regression is to discover the function that associates the input variables (x) with the continuous output variable (y). If we want to predict a number, we use regression. We could predict age, salary or house prices given particular features we observe [34].

- **Types of Regression Algorithms:**
    - *Simple Linear Regression:* Simple Linear Regression, also called regression, is the key method used to explore the influence of one factor on another. It lets you make a straight connection between two things such as height and weight for a person. With this technique, we can see the influence of a variable upon another variable [35].

- *Multiple Linear Regression:* Multiple Linear Regression is a kind of Simple Linear Regression that is extended to several independent variables. Assuming a linear relationship, it simulates how two or more independent variables relate to a dependent variable. The model equation is y = a0 + a1x1 + a2x2 +... + anxn, where x's are independent variables and b's are coefficients [35].
- *Polynomial Regression:* This technique is used when the link between variables isn't a line. In linear regression, each trend is shown by a line, but polynomial regression uses a range of curves (such as x^2, x^3 and other exponential forms) to track data with more distracting changes. As a result, it can point out designs that are not noticeable if we rely solely on a straight-line tracker [35].
- *Decision Tree Regression:* The Decision Tree Regression technique is used to predict numerical results by creating a tree structure. It explains every decision step by step, ending up with a predicted value at the end of each path. Using logistic regression on difficult datasets is not complicated, but this approach can cause the model to make wrong predictions with unfamiliar data because it focuses on the training data too much [35].
- *Random Forest Regression:* Random Forest Regression uses various decision trees to help make predictions. It reduces its dependence on just one tree and this makes the prediction more reliable and stable. Minimizing errors and overfitting are better with this method than if you only use a single tree [35].
- *Ensemble Method:* Using multiple models to join results and see an improved outcome is called ensemble method. They find better outcomes by using several models compared to just one. Other machine learning algorithms are Random Forest, Gradient Boosting and Bagging. Often such methods are better than single models as they bring together predictions and remove errors.

c. **Forecasting:** Forecasting is the practice of projecting future tendencies, using information from the past and the present. People often use it when forecasting the weather or predicting sales [35].

ii. **Semi-supervised learning:** Semi-supervised learning uses information from both datasets that have answers and those that don't. It is most helpful when getting all the data is either difficult or too costly. The computer uses the samples from the small data collection to help with the larger, unlabeled data [36].

iii. **Unsupervised Learning:** With unsupervised learning, computers use raw data that hasn't been arranged or given special tags. They search for and discover patterns or collections among those things on their own.

It can play a key role in catching fraud thanks to spotting unusual actions that are out of the ordinary. You can use it to select places for emergency centers such as hospitals, in areas likely to experience accidents. Accident hotspots are discovered by the computer, grouped into clusters and then the computer proposes the best location in every cluster to put a hospital, so more people can be helped in less time [37].

- **Types of Unsupervised Learning Algorithms:**

a. **Clustering Algorithms:** In the absence of pre-existing knowledge regarding group membership, these algorithms aggregate data points that exhibit similarity. For instance, K-means clustering can be employed to differentiate distinct consumer segments based on their purchasing behaviours.

- *K-Means Clustering:* In order to reduce the variation within each cluster, the method uses similarity metrics to partition the data into 'k' clusters [37].
- *Hierarchical Clustering:* A hierarchical representation resembling a tree is generated to depict clusters, in which data elements that are similar are organized together at varying degrees of granularity.
- *DBSCAN (Density-Based Spatial Clustering of Applications with Noise):* Cluster identification is performed by DBSCAN using data density to categorize points as core, border, or noise points [38].

b. **Dimensionality Reduction Algorithms:**

These algorithms are implemented to decrease the feature count of a given dataset while maintaining critical information. For instance, PCA can be utilized to extract meaningful features for facial recognition in image processing.

- *Principal Component Analysis (PCA):* PCA reduces the dimension of high-dimensional data while preserving the maximum amount of variance.
- *t-Distributed Stochastic Neighbor Embedding (t-SNE):* t-SNE is used for visualizing high-dimensional data by preserving local structures and emphasizing clusters [38].

c. **Association Rule Learning:**

In the context of large datasets, this category of algorithm discerns patterns and relationships. In the retail industry, for instance, the Apriori algorithm can assist with strategic product positioning by revealing which items are frequently purchased together.

- Apriori Algorithm: Frequently implemented in market basket analysis, this algorithm mines frequent item sets from transactional databases in order to identify associations between items [39].

iv. **Reinforcement Learning:** Reinforcement Learning trains machines via the actions they take. The model experiments with several techniques to see how each one works. Getting good results pays off; failing does not. By studying both victories and defeats, the model finds the effective way to reach the specified target. It's a bit like learning through experience and discovery [40].

Example: Think about an infant trying to learn how to walk. When she takes the chocolate, she feels happy - something positive happens. She gets upset when she can't reach the chocolate because she has hit a chair and cannot pick it up. The baby finds out which direction gives them the reward.

This form of learning means the model (ifs the baby's mind) explores different solutions, understands the results and improves over and over to achieve success [40].

1.3.2. Machine Learning in Healthcare

Using machine learning helps doctors and their teams to make wiser decisions in medicine. It considers a broad range of medical information, obtained via fitness trackers, genetic tests, health records and scans, to look for useful trends, predict outcomes and provide treatment advice. The outcome is faster support, more accurate diagnoses and treatments adjusted for every patient [41].

Doctors can do more with patient care and medical data thanks to machine learning. This field program computers to use human-like thought and choice. Technology is used in hospitals to arrange patient data, find trends in health and suggest suitable treatments. More and more medical establishments realizing the usefulness of machine learning opens up fresh employment opportunities [42]. IDC expects India's AI market will expand by more than 100% between 2020 and 2025.

With more growth in the sector, startups will need more AI knowledge and extra jobs in healthcare will also be created. When you look through the details, "artificial intelligence" and "machine learning" are based on everyday programming and math. After you understand the main points, you can move forward and look into interesting jobs in healthcare and related fields. It gives experts fast career growth, contentment and a wide range of development opportunities [43].

1.3.3. Rise of ML in healthcare settings

With the continuous advancement of technology, machine learning presents a promising prospect in the healthcare sector to enhance diagnostic precision, individualize medical care, and discover innovative resolutions to longstanding challenges. By programming computers to make predictions and connections and to extract vital insights from massive quantities of data that healthcare providers might otherwise overlook, machine learning can have a direct effect on the health of your community [44].

The objective of machine learning is to generate medical insights that were previously inaccessible and enhance patient outcomes. It enables the validation of the reasoning and decisions of physicians via predictive algorithms. Consider the scenario in which a physician prescribes a particular medication to a patient. Consequently, machine learning can verify the efficacy of this treatment regimen by identifying a patient who has undergone the identical intervention and shares a comparable medical history [44].

1.4. Healthcare applications of machine learning along with the Internet of Healthcare Products

One must depend on a dataset of patient information that is always changing when using machine learning in healthcare. Medical experts may use this data store to find patterns that will help them detect new illnesses, evaluate risks, and predict how treatments will work. Integrating medical devices into a centralized network is a practical way to aggregate large amounts of data, especially considering the large number of patients and the broad variety of medical technologies utilized for data collecting [45].

Interconnected medical equipment and apps that may communicate over internet networks make up what is known as the Internet of Medical Things (IoMT). Nowadays, a lot of medical equipment has Wi-Fi built in, so it can talk to other devices on the same network or even in the cloud. With this feature, a lot of things become possible, such keeping medical records up-to-date, monitoring data from wearable devices, and remote patient monitoring. For example, ambulances all throughout India are getting sensors that connect to the Internet of Medical Things (IoMT), as mentioned in a study on the Indian healthcare system by PWC The Bengal Chamber. Medical staff at healthcare institutions may now access critical patient records and data prior to the patient's arrival, thanks to this deployment. In the near future, the IoMT is expected to see exponential expansion because to the widespread use of wearable devices and internet-enabled medical instruments [46].

1.4.1. Types of AI relevant to healthcare

Artificial intelligence encompasses machine learning as well. Although there are several forms of AI, the healthcare business may benefit from certain forms. Healthcare machine learning experts often work on improving healthcare records and other administrative systems, mining massive clinical data sets for patterns, and developing tools to aid doctors in patient care [47].

Among the most popular forms of AI employed in these key domains are:

i. **Deep learning and neural networks in machine learning:** Neural networks are a type of machine learning that aims to mimic the neural networks seen in the human brain. These networks are referred to by several names, such as simulated neural networks (SNNs) and artificial neural networks (ANNs). In healthcare, ANNs may mimic human reasoning for diagnosis by generating computer-generated results that are comparable to the latter [48].

   Deep learning an ANN's capacity to get knowledge from large datasets is based on ANNs. Using deep learning, medical professionals may examine magnetic resonance imaging (MRI) and other imaging studies for anomalies. Although medical professional's work is still crucial, this enables them to diagnose patients more quickly and start treating them, which improves their performance [48].

ii. **Natural language processing:** NLP is a branch of machine learning that aims to make computers better at comprehending, analysing, and producing natural language. Natural language processing enables interaction and communication with the computer. One use of NLP in healthcare is the extraction of data from medical records [48].

iii. **Physical robots:** Just what they sound like: robots that can interact with a doctor in person. Surgical robots can assist doctors with intricate operations that call for pinpoint accuracy. The less invasive nature of robotic surgery often leads to better results with fewer problems [48].

iv. **Robotic process automation:** When it comes to data input and other manual operations, robotic process automation uses machine learning to imitate human behaviors. Organizations in the healthcare industry automate these processes with the use of machine learning. Doctors and hospital management will have more time to focus on what really matters when this is taken care of [48].

1.4.2. Applications of machine learning in healthcare

Despite the constant emergence of novel machine learning applications, the majority of these applications in healthcare focus on enhancing the standard of care and the health outcomes for patients. Machine learning has many potential applications in healthcare, so you may focus on one area if you choose. Gaining familiarity with the many machine learning healthcare applications (such as the ones mentioned below) might assist in selecting the module or specialization that aligns most closely with your interests and aspirations [49-50].

- **Improve trauma-care response:** There may be less delay in providing life-saving care to patients by developing sensors and equipment that can transmit their critical vital signs to the hospital prior to their arrival by emergency transport, such as an ambulance [49-50].
- **Disease prediction:** Machine learning allows you to discover patterns, establish associations, and derive conclusions from massive datasets. Predicting community-wide illness outbreaks and monitoring patient disease-causing behaviors are examples of what this encompasses [49-50].
- **Visualisation of biomedical data:** Using machine learning, biomedical data, such as RNA sequences, structures of proteins, and genetic profiles, can be represented in three dimensions [49-50].
- **Improved diagnosis and disease identification:** Discover novel symptom patterns that have not been seen before and compare them to bigger datasets to detect illnesses at an earlier stage [49-50].

- **More accurate health records:** Ensure that all medical institutions have up-to-date, accurate, and easily transportable patient records, doctors, and personnel [49-50].
- **AI-assisted surgery:** Assist surgeons with complicated tasks as they work, improve their visibility of the operating field, and demonstrate how to execute operations [49-50].
- **Personalised treatment options:** Machine learning allows you to examine data from several modalities and, using all of the available treatment choices, make judgments that are specific to each patient [49-50].
- **Medical research and clinical trial improvement:** Using ML, you can improve clinical trial participant selection, data collecting, and analysis [49-50].
- **Developing medications:** Machine learning may help you find new drug development routes and create creative treatments for a wide range of medical issues [49-50].

1.4.3. Ethics of machine learning in healthcare

Although ML offers healthcare a fresh and exciting possibility, it also brings up significant ethical issues. First, when medical decision-making is delegated to smart devices, privacy, transparency, and reliability issues surface. The diagnostic process may be made more stressful and uncertain by the fact that, unlike with a doctor, machines cannot talk about a patient's condition. Furthermore, rather of a machine, individuals would prefer to hear terrible health news from a trusted physician [51-52].

Additionally, medical facilities can want to avoid accountability for a misdiagnosis made by AI, and patient diagnostic mistakes are most likely unavoidable. Prediction accuracy may be impacted by racial and gender characteristics, and machine learning engineers may unintentionally create biased algorithms [53–54]. To prevent unforeseen consequences, regulators and healthcare providers must establish early norms, accountability, and restrictions on the application of machine learning in healthcare [55].

1.5.Link machine learning attributes to healthcare framework

Fig. 2 showcases the diverse range of intelligent and compassionate characteristics linked to the ML culture and its vast range of healthcare services. Included in this are the many digital and intelligent technologies used in healthcare, such as cloud data performances and artificial intelligence. Creating EMRs is a tremendous boon to the healthcare industry, and it doesn't break the bank. Intelligently created reports, digital notes, records maintenance, etc. are a few more significant areas where ML concepts demonstrate their value in healthcare. In order to keep an eye out for possible epidemics, healthcare facilities throughout the globe are using ML systems [56].

By compiling information from the web, satellite data, and social media updates in real-time, this digital system may predict when diseases will spread [57-58]. It may be a lifesaver for developing nations without proper medical infrastructure.

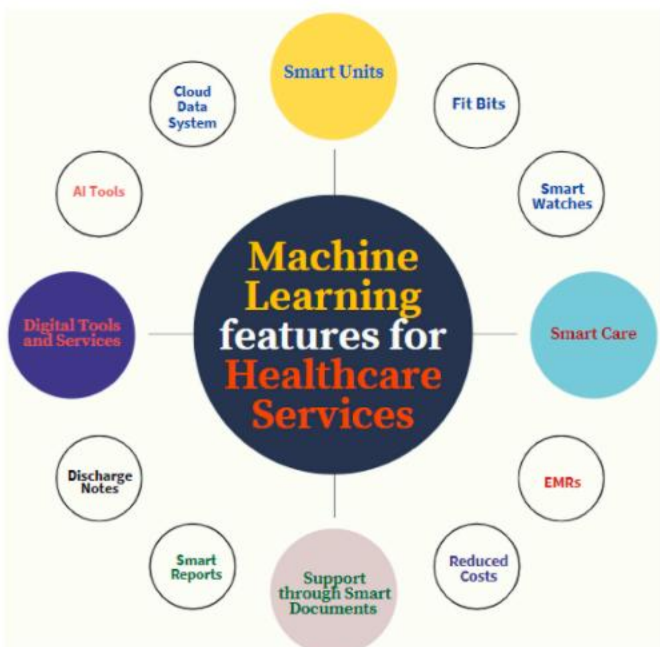


Figure 2. Machine learning capabilities tailored to the healthcare sector**.**

A lack of access to the right healthcare practitioner, lengthy and overly complicated appointment processes, excessive concern of costs, and long lineups are all symptoms of underlying problems that ML and similar data-driven approaches aim to solve. Traditional organizations have been dealing with similar problems for decades, and ML approaches are already contributing to the answer. This is due to the fact that ML systems' strength their extensive databases and clever search algorithms do very well when faced with optimization or pattern matching problems [56–57].

Merging empathy with a profit-generating aim is essential for powerful ML technologies to distinguish themselves from conventional systems in hospital operations management. The goal is to determine the best course of therapy based on each patient's individual medical history, lifestyle choices, genetic information, as well as pathology testing. This is a very challenging and timeconsuming process. Naturally, the problem will demand the best artificial intelligence techniques, including probabilistic graphical models, neural networks with deep connections, powered by AI search algorithms/advanced reinforced learning, and semi-supervised learning. By using machine learning (ML) to healthcare, they may make judgments more rapidly by employing insights gleaned from historical data, such as details on genetic abnormalities, family histories, and illnesses [58-59].

More and more people are using ML for anything from social media recommendation systems to factory process automation because to the proliferation of affordable hardware and cloud computing. The healthcare business is also one that adapts to new circumstances. Due to the large amount of data collected for each patient, ML algorithms in healthcare have great promise [60-61]. The flip side is that they may save money and provide a better experience for patients by planning ahead and suggesting comprehensive treatments. The healthcare business is fortunate to have ML. The medical history of a patient, their family, and any prior treatments all include large amounts of unstructured data. By analyzing patients' medical records, ML helps doctors anticipate serious health problems [62–63]. The shift to healthcare management and delivery based on information has been expedited by the growth of this technology.

Information systems driven by ML are essential to the modern interdisciplinary effort to enhance healthcare outcomes via better imaging and genetically-based personalized treatment models. Additionally, ML will produce outcomes far more quickly, enabling therapy to commence earlier, even though a healthcare practitioner and an ML algorithm would likely arrive at the identical conclusion using the same dataset. Another perk of using ML approaches in healthcare is that it eliminates some human intervention, which in turn reduces the possibility of human mistake. This is particularly the case when it comes to process automation tasks, as human error is most prevalent in mundane, repeated tasks [64–65]. When it comes to diagnosing an illness, deciding on a course of therapy, spotting any problems, and improving the overall efficiency of patient care, clinical decision support technologies are invaluable. ML's rising popularity in recent years is due in large part to the fact that it is a strong approach that helps doctors perform their jobs faster and more accurately, which in turn lessens the risk that they would prescribe inefficient therapy or make an inaccurate diagnosis [66]. This is because many data points, including medical pictures, have been digitized and electronic health records have been more widely used. In the medical field, X-rays and other similar pictures remained analogue for a very long time.

Anomaly identification, case categorization, and sickness research have all been hindered by this. Thankfully, ML and other types of data analysis have found more substantial prospects as a consequence of the industry's digitization. In order for ML to find patterns and draw conclusions faster, healthcare data must be prepared. Annotation over the input is the human-run process that identifies and labels dataset components. Data analysis, rule writing, and machine performance optimization are all areas in which clinical professionals excel. On the other hand, accurate and meaningful annotation of the data is crucial for healthcare ML systems to learn quickly and effectively by extracting key ideas with suitable context. Performing surgical procedures requires pinpoint accuracy, the capacity to quickly adjust to new circumstances, and a steady hand over a long period of time [67-68]. A potential future use of machine learning in healthcare is the ability for robots to carry out surgical procedures, even though trained humans already possess all of these abilities. Using historical data on active pharmaceutical ingredients and their effects on the body, ML systems may model how an active ingredient might work in a different, comparable setting [69-70].

A lot of resources, including time and money, are needed for research and clinical trials. In addition to providing reliable results, ML-based predictive analytics help keep clinical trial budgets and timelines in check. Machine learning (ML) technology has many more uses beyond only finding people to participate in clinical trials; it can also access their medical information, keep tabs on them while they're in the study, choose the most appropriate testing samples, and even remove data-based mistakes. By using ML, healthcare personnel may enhance their industry, simplify various activities, and, in the end, save lives. Machine learning (ML) is essential for prevention purposes in addition to its direct applications in healthcare. This innovation enhances surveillance by letting experts see problems that may not be obvious at first glance but might endanger our lives if left unchecked. Emerging illnesses, pandemics, and pollution are only a few of the many potential threats to human health in the future [71–73]. On a worldwide scale, healthcare institutions may use ML to anticipate issues that have not yet affected the patient. Because of this, medical professionals may provide remedies that either prevent the issue from happening or greatly mitigate its impact once it does. Because early diagnosis is so crucial in cancer therapy, it is of utmost importance. With the help of ML, cutting-edge healthcare innovations like smart imaging have become a reality. One of the things that healthcare depends on significantly is patient records. Enhancing and streamlining patient data may empower healthcare providers to foresee future challenges, address current ones, and evaluate individual cases. A patient's medical history includes not only their current and past illnesses, but also information on their mental and physical well-being. With the help of ML, smart patient records are starting to materialize and are finding extensive use in healthcare. The value of smart patient records to medical practitioners is enhanced in almost every way due to their simplification and streamlining [74-75].

1.6. Pillars of machine learning for healthcare

There are a number of ways in which the healthcare sector has benefited from the idea of ML and its flexible capabilities. The many quality pillars and enablers that aid and care for healthcare units are examined in Fig. 3. The well-known ML idea has further expanded its services for the benefit of society via healthcare, with features such as the capacity to anticipate outbreaks, diagnose medical imaging, modify behavior, record patient data, etc. When these services are needed in healthcare procedures, the important foundations are undoubtedly provided by the efficacy and performance of these ML features [76-78]. ML entails feeding computers data and an algorithm in order to train them to identify patterns. Disease detection is a challenging manual process; ML is crucial in identifying the patient's illness, tracking his vitals, and suggesting preventative measures. It may vary from relatively harmless conditions to deadly ones like cancer, which can be hard to see in its early stages [77, 79].

A application case for ML in healthcare may include learning about and forecasting issues related to mental health on a global or sector-specific scale. As a result, mental health professionals are better able to pinpoint which populations are most vulnerable to catastrophic events like pandemics. In order to choose molecules with appropriate physicochemical properties and biological activity, it may evaluate their absorption, distribution, metabolism, and excretion characteristics [80-82]. Scholars and practitioners in the medical field are now using crowdsourcing to get access to massive amounts of data that individuals have voluntarily contributed. The future of medicine is profoundly affected by such real-time health data.

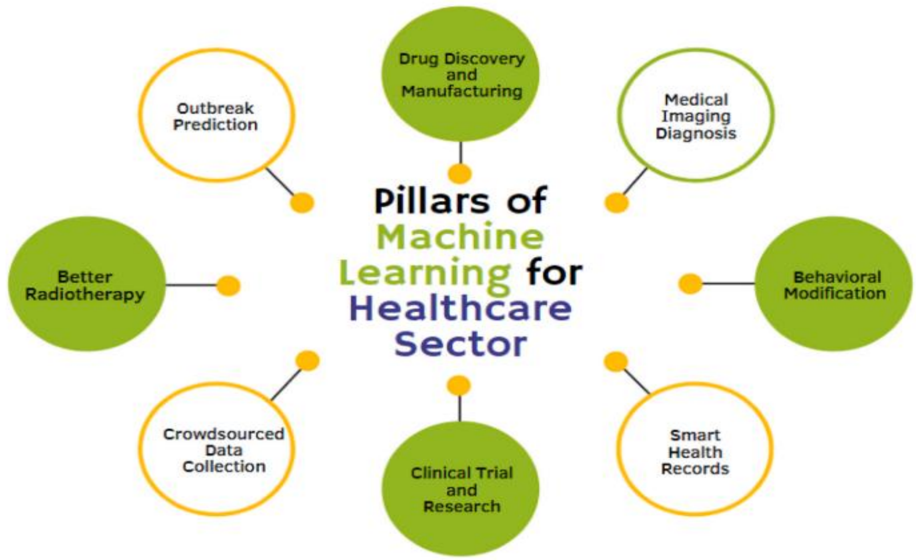


Figure 3. Foundations of healthcare-related machine learning**.**

With this gear, we can sift through mountains of data collected from sources like social media, satellites, websites, and government databases in real time. From malaria outbreaks to other major infectious disease forecasts, networks may help make sense of this data. It takes a lot of effort and money to keep health records up to date and accurate. When it comes to streamlining the data entry process, this technology is crucial. Still, because to the need for human intervention, the majority of procedures still take an excessive amount of time to complete. Here is where machine learning comes into play. They say it will save costs, save time, and simplify things [83-84]. Machine learning (ML) may help move healthcare away from a reactive and toward a preventative model by providing personalised treatment suggestions. With its help, doctors will be able to treat each patient with a personalized plan that takes into account their specific symptoms and characteristics. Consequently, fewer people may likely experience adverse effects from their prescribed drug. Disease outbreaks may be better predicted and monitored with the use of ML algorithms in healthcare. Also, ML may lessen the negative effects of epidemics [85-86].

Machine learning has the potential to streamline clinical trials and enhance the drug development process. Pharmaceutical businesses face a multitude of challenges in this domain. Clinical trial planning has always been a laborious process due to the large number of variables that must be considered. This means that there are a number of criteria that prospective clinical trial participants must pass through in order for the findings to be reliable. In order to ensure the safety and efficacy of the treatments, this technology continuously monitors and analyzes vast amounts of data [87-88]. Machine learning allows computers to autonomously understand ideas, analyze data, and provide the outputs that users want. Many different types of learning techniques, including supervised and unsupervised learning, are used by ML models to learn how to understand data via clauses and conditions. This makes them a good fit for making predictions and recommendations. Also, by notifying patients about their appointments, report collecting, and other activities in a timely manner, ML helps optimize patient engagement and recovery.

When it comes to medical applications of ML, illness detection and diagnosis are among the most important. While issues like cancer and inherited disorders are notoriously hard to spot in their early stages, they may be identified with pinpoint accuracy with the help of well-trained ML solutions [89-90]. ML is finding several uses in healthcare, including problem solving. Patients' quality of life is enhanced when they are able to get the right treatment, and the health care system may guarantee effective use of resources by providing patients with appropriate therapies. ML has the potential to support a value-based strategy for cancer treatment, which highlights the significance of having access to linked health data and working together among different public and private stakeholders. The administrative and organizational parts of healthcare delivery, including managing patients and beds, conducting remote monitoring, scheduling appointments, and compiling duty rosters, are greatly improved by this technology. On a daily basis, healthcare staff are unable to provide the care that patients need because they are too busy with administrative tasks, record maintenance, and claims processing.

Automation and the removal of human involvement in places may be achieved via the deployment of ML models [91-93]. Many patients with chronic diseases, such as diabetes, go for years without experiencing any symptoms at all. Because of this, individuals often find out about their diabetes after it has progressed too far to treat. But ML models might help us prevent these kinds of situations. We may now use ML-based models to help us recognize these unconscious habits and make necessary changes to our way of life. Something as simple as a wristband or an app that tells us to get up and walk about after sitting for a while may fall into this category [94, 95]. The quick development of COVID-19 vaccines was only possible using data-driven development approaches. The accuracy of radiology diagnoses was enhanced with the use of image recognition algorithms for the detection of small abnormalities, such cancer metastasis.

Social media postings and wearable medical records are two examples of the types of data used to predict health problems and illnesses. Many uses, including sensor alarms, need a decrease in false positives.

A false positive happens when a test incorrectly identifies the presence of a condition, such an illness, when in fact it isn't. Diagnostic data is enhanced by using technologies to reduce false positives and false negatives [96-97]. With the advent of ML came several useful solutions that helped entrepreneurs make their firms more lucrative and customer-centric, like telemedicine, self-driving vehicles, hyper-targeted marketing, and many more. ML has now become an integral component of many sectors. Medical practitioners may benefit greatly from ML's array of tools and approaches, which have a direct bearing on patient outcomes. Fields that work with massive datasets may reap the advantages of ML software's clever prediction algorithms right away [98-99]. High cholesterol levels, obesity, cancer, diabetes, heart disease, and mental health issues are all greatly increased when people are not physically active. Conversely, it is possible to avoid these illnesses and halve death rates with regular physical activity of at least one hour each week. Customization of the advice to each person is a crucial component. With ML, personalized coaching and reward systems that provide suggestions depending on daily activity performance may be provided in real-time and on an ongoing basis. Some people need an external push to get them started, others are performing some exercise but might use more motivation to step up their game, and so on. Machine learning (ML) helps medical professionals by learning from large amounts of data and making predictions and forecasts. Some of the most investigated ailments are ML tools, cardiovascular disease, and problems of the brain system. An important step toward better early detection and diagnosis is the ability of self-trained systems to learn using both supervised and unsupervised approaches. To function properly, self-trained systems need ongoing interaction with data from clinical studies, suggesting that human intervention is intrinsically related to ML. Finance and banking is a perfect area to use AI and ML since there is a lot of structured data compared to other sectors. Investment banks pioneered the application of AI innovations many years ago. The industry has come a long way since then, improving the lives of both practitioners and clients. Machine learning (ML) is an emerging area of computer science that teaches computers to accomplish more complex tasks than just following rules. The errors of others may teach them a thing or two. It enhances the quality of patient treatment and is used for predictive analysis. Predictive analysis is the process of using data and information to make predictions about the future [100].

1.7. Research Problem and Objectives

In the field of health care, it is a massively researched topic. There are a lot of studies looking at IoT, ML, and AI. Nevertheless, there is a substantial additional hurdle for ML-based medical health care applications when contrasted with conventional IoT-based health care application systems [101-103]. Currently, the app's only feature is the ability to see data from sensors visually. Installing sensors in a wide variety of devices makes it very difficult to maintain, monitor, and power all of them at once [104–106]. There are now known research gaps as a result of the aforementioned fields' analyses.

- Vital signs, medical rules with active contexts can be used to identify a patient's critical state remotely [11-14], [17-18], [35-36], [44-45].
- Patients with chronic diseases also having autism spectrum disorder (ASD) who are monitored by healthcare professionals and AAL devices has no real-time health status assessed using ML models [15-19], [21-22], [37], [42-44].
- Big data analysis in unstructured and unbalanced datasets can be handled more effectives [20-22], [28-30] [38], [46-48].
- A real-time ML-based analytical information system for monitoring vital signs is lacking in the current medical equipment using both local and cloud-based categorization models [23-27] [31-34], [54-55].

Motivated by the lack of empirical research towards all the above research questions we come up with following objectives have been identified.

1. To analyze existing machine learning based vital sign monitoring systems.
2. To propose a novel real-time vital sign monitoring system using machine learning.
3. To evaluate the performance of the proposed system using few performances metrics.

1.8. Evaluation Methodology

The suggested innovative real-time vital sign monitoring system that makes use of machine learning is going to be evaluated using a rigorous approach that covers all the bases in terms of performance, efficacy, and dependability. To fill in the gaps and accomplish the goals in the existing study, as well as to ensure the safety of the device, this technique will test how well the Smart Patient Monitoring and Recommendation (SPMR) architecture works [101-102].

1.8.1. Data Collection and Preparation

Gathering varied and representative datasets pertaining to monitoring vital signs, patient health condition, contextual activities, and medical guidelines is the first step of the assessment approach. To accurately reflect real-world scenarios and variations in medical conditions, it is essential for these datasets to encompass both structured and unstructured data. To ensure the data remains consistent and compatible for the training and testing of machine learning models, various preparation methods are employed to clean, standardize, and convert the data [103-104].

1.8.2. Machine Learning Model Training

The subsequent phase involves training machine learning models using the acquired and refined data. The predictive component of the SPMR framework employs advanced techniques, particularly focusing on Deep Learning (DL) and CCE Optimization, to effectively train its models. The models utilize historical data and employ supervised learning techniques for training. This enables a comprehensive understanding of trends, correlations, and predictive connections among patient health outcomes, medical guidelines, and vital signs [105].

1.8.3. Performance Metrics

The evaluation of the real-time vital sign monitoring system, which utilizes machine learning, is conducted through various performance measures:

- Precision: Assesses the general correctness of the suggestions produced by the models.
- Accuracy: is a metric that evaluates the proportion of true positive results against the total number of positive predictions made.

- Recall: It computes the quantity of correctly identified positive cases as a fraction of the number of all actual positive occurrences.
- The F1-score is a metric that balances accuracy and recall, giving a fair overall measure of how well the model performs.
- An important measure for evaluating the differentiating ability of a model among more than two classes is the area under the receiver operating characteristic curve, which is known as AUC-RO.

The results are derived from the test datasets and cross validation which confirms their reliability and universality [106-108].

1.8.4. Comparative Analysis

We conduct an analysis of the proposed real-time vital sign monitoring system in comparison to both established machine learning systems and traditional Internet of Things (IoT) healthcare applications to ascertain its relative performance. This study evaluates various aspects: accuracy, predictive power, real-time monitoring and efficiency. However, it does so by drawing comparisons with similar models. Although there are many factors to consider, the findings suggest a nuanced understanding is necessary because the systems differ in their operational capabilities. This indicates that while one system may excel in accuracy, it could fall short in efficiency [109].

1.8.5. Security and Reliability Testing

The evaluation method additionally includes examining the reliability and security aspects of the SPMR framework. The evaluation of the system's capacity to endure potential security threats, data integrity issues, and operational disruptions is conducted through stress testing and simulated attack scenarios. To ensure that the real-time monitoring system remains operational under various loads and conditions, reliability testing is performed [120].

1.8.6. Performance Evaluation

The metrics, in conjunction with the results derived from comparative analyses, security assessments and reliability evaluations, function to gauge the overall performance of the proposed system. This review seeks to illustrate the efficacy of a real-time vital sign monitoring system that employs machine learning to enhance healthcare management, decision-making processes and patient outcomes [121].

1.9. Thesis Contributions

This work introduces significant advancements within the realm of healthcare monitoring systems, particularly emphasizing real-time vital sign tracking via the utilization of machine learning and IoT technologies. The contributions can be encapsulated in the following manner:

- **Development of Smart Patient Monitoring and Recommendation (SPMR) Framework**

This work's main contribution is the introduction of a Smart Patient Monitoring and Recommendation framework (SPMR). The suggested framework aims at proactively providing input and enhancing continuous monitoring of the patient's health condition by deeply integrating complex technologies such as deep learning, cloud-based analytics, and IoT principles. Despite the adoption of IoT in the health sector, it tries to bridge the research gaps and overcome the pitfalls of existing IoT-based healthcare applications through autonomously monitoring patients using machine learning algorithms for personalized recommendations [121-123].

- **Novel Approach to Vital Sign Monitoring**

A novel approach is presented for monitoring the vital signs through the integration of machine learning models within the SPMR framework. The approach improves the accuracy, reliability, and speed of the vital sign data analysis, enabling quick health issue detection, personalized treatment proposals, and better outcomes for the patient.

- **Evaluation and Comparative Analysis**

A widespread evaluation approach has been developed to assess the proper working of the SPMR framework. The research gives insight into the precision, recall, accuracy, F1 score, and AUC-ROC measurements for the machine learning approaches which were employed in real-time monitoring. Furthermore, the analysis of the comparison of the SPMR framework to already existing health monitoring systems showcases its efficacy and the various developments made.

- **Security and Reliability Testing**

This work makes a significant contribution to literature on healthcare cybersecurity by reviewing security and reliability tests on the SPMR framework. The study combines stress tests, reliability testing, and simulations of attack cases to evaluate its ability to protect from security threats, operations failures, and threats to information integrity. This allows the system to sustain continuous and periodic monitoring capabilities [124-126].

- **Advancements in Healthcare Management and Decision-Making**

The findings from this research contributed to significant improvements in healthcare administration and decision-making. The incorporation of deep learning, cloud analytics, and IoT concepts in the SPMR framework provided a holistic approach for real-time vital sign monitoring, enabling caregivers to optimize patient care via informed decisions and timely interventions [127-129].

1.10. Thesis Organization

The organization of my work is based on the studies that I undertook during my research journey. This outlines the contents of each of the chapters and their description.

i. **Introduction**

   a. *Background and Context of Real-Time Vital Sign Monitoring*

      - Explain the operations of continuous monitoring of the vital signs and their importance in healthcare.
      - Examine the obstacles encountered in conventional healthcare monitoring systems.
      - Discuss how machine learning and IoT technologies contribute to enhancing real-time monitoring capabilities.

   b. *Problem Statement and Research Objectives*

      - Identify the research issue concerning the shortcomings of current healthcare monitoring systems.

- Articulate the precise aims of the study, encompassing the creation of the Smart Patient Monitoring and Recommendation (SPMR) framework.

ii. **Literature Review**

a. Overview of Machine Learning in Healthcare Monitoring

- Deliver an in-depth analysis of the utilization of machine learning within the healthcare sector.
- Examine the progression of healthcare monitoring applications that utilize IoT technology.
- Examine pertinent research and progress in the area of real-time vital sign tracking through the application of machine learning, IoT, and the incorporation of Cloud Analytics and Deep Learning in healthcare monitoring and recommendation systems.

c. Derived from Research Papers:

- **Sundas, Amit**, et al. "Evaluation of Autism Spectrum Disorder Based on Healthcare by Using Artificial Intelligence Strategies." (Journal of Sensors, 2023)
- **Sundas, Amit**, and Sumit Badotra. "Comprehensive Study of Machine Learning-Based Systems for Early Warning of Clinical Deterioration." (International Journal of Performability Engineering, 2022)
- **Sundas, Amit,** et al. "Sensor Data Transforming into Real-Time Healthcare Evaluation: A Review of IoT Healthcare Monitoring Applications." (2023 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics)

iii. **Proposing a Novel Real-Time Vital Sign Monitoring System Using Machine Learning**

a. Development of Smart Patient Monitoring and Recommendation (SPMR) Framework

- Outline the elements of the SPMR framework, encompassing Deep Learning (DL), cloud-based analytics, and IoT principles.
- Discuss the methods employed for gathering and organizing data to train machine learning models.
- Detail the approach for assessing performance indicators, performing comparative evaluations, and examining security and dependability.

b. Derived from Research Papers:

- **Sundas, Amit**, et al. “Smart Patient Monitoring and Recommendation (SPMR) using Cloud Analytics and Deep Learning". IEEE Access.
- **Sundas, Amit**, & Badotra, S. "Recurring Threats to Smart Healthcare Systems Based on Machine Learning." (ICRITO, 2022)

iv. **Performance Evaluation of the Proposed Real-Time Vital Sign Monitoring System**

a. *Performance Evaluation of SPMR Framework*

- Provide the outcomes of precision, accuracy, recall, the F1 score, and AUC-ROC indicators for the machine learning models employed in real-time monitoring.
- Examine the comparative outcomes in relation to current healthcare monitoring systems.
- Examine the results of testing for security and reliability.

b. *Interpretation of Results and Comparative Analysis*

- Analyze the results from the performance assessment and comparative study.
- Analyze the advantages and disadvantages of the SPMR framework in relation to current systems.
- Emphasize the significance of the findings for the administration of healthcare and the processes involved in making informed decisions.

c. *Derived from Research Papers:*

- **Sundas, Amit**, et al. "Streamlined Patient Care with Smart Monitoring and Deep Learning-Based Recommendations." (ICCS-2023)
- **Sundas, Amit**, et al. "Optimizing Length of Stay Prediction After Intubation: An Advanced Machine Learning Model with Real-time Vital Sign Integration"", In 2023 Seventh International Conference on Image Information Processing (ICIIP -2023), Jaypee University of Information Technology, Waknaghat, District Solan, Near Shimla, Himachal Pradesh, India. (https://www.juit.ac.in/iciip_2023/).
- **Sundas, Amit**, et al. "Investigating the Role of Machine Learning Algorithms in Predicting Sepsis Using Vital Sign Data." (IJACSA, 2023)
- **Sundas, Amit**, et al. "Internet of Health Things-enabled Monitoring of Vital Signs in Hospitals of the Future." (First International Conference on Applied Data Science and Smart Systems)

v. **Securing Healthcare Infrastructures: Machine Learning Solutions for System Integrity**

a. Introduction of HealthGuard Security based on Machine Learning-based Detection Approaches:

- *Recognize the security challenges encountered by SHS, such as disruptions to device performance, the introduction of fraudulent data, and the tampering of medical devices by harmful entities.*
- *Highlight the essential requirement for strong security protocols to safeguard sensitive medical information and maintain the integrity of SHS functions.*
- *Detail the assessments performed to determine HealthGuard's capability in protecting against three different types of malicious attacks.*

b. Derived from Research Papers:

- **Sundas, Amit**, et al. "HealthGuard: An Intelligent Healthcare System Security Framework Based on Machine Learning." (Sustainability, 2022).

vi. **Conclusion and Future Directions**

a. Summary of Thesis Contributions

- Highlight the main achievements of the research, focusing on the creation of the SPMR framework and the progress made in real-time monitoring of vital signs.
- Examine the importance of the study in enhancing healthcare methods.

b. Future Directions and Recommendations

- Propose possible avenues for further investigation stemming from the results and constraints recognized.
- Offer suggestions for improving the SPMR framework and its uses in the healthcare sector.

vii. **References**

Include all cited references from the research papers and sources used throughout the thesis.

Chapter 2: Literature Review

Overview

This chapter on historical research provides a comprehensive overview of applying machine learning techniques to healthcare monitoring systems. First, it presents a broad case study of the widespread application of machine learning in healthcare, which displays machine learning's transformative role across different areas of patient care and medical diagnosis. Underlying this chapter is an analysis of the evolution of IoT-based health monitoring applications by comparing the progression of sensor technology and data gathering processes that have radically transformed real-time patient monitoring. It speaks about how these IoT devices, combined with machine learning algorithms, improved the accuracy, efficacy, and safety of vital sign monitoring. Furthermore, it critically discusses other studies and innovations related to real-time vital sign monitoring based on machine learning and IoT. The section looks at key methodologies, algorithms, and frameworks that progress managerial monitoring systems, and focus on predictive analysis, anomaly detection, and customized patient care.

2.1. Introduction

Data creation and sharing is amazing in the healthcare sector and is foreseen to cross over 1,656 zettabytes by 2025 [1]. With proper research and analysis, the clinical, financial, and operational value of these healthcare data sets can be unlocked. (ML) Artificial intelligence is providing another way to process healthcare data in the current settings. More recently, multiple applications in healthcare based on machine learning have been introduced to enable various healthcare functions, such as early diagnosis, disease detection, development of a cure, and planning of treatment [2]. The identification and evaluation of clinical markers through ML has undoubtedly sped up and improved the accuracy of medical treatment [3]. Personalized medication and care driven by ML's ability to extract the critical feature set necessary for focused analysis may improve outcomes, save clinic expenses, and promote stronger rapport between physician and patient. There will be a $34 billion market for ML solutions in healthcare by 2025 [4-5]. ML is mainly applied in the healthcare sector to process patient data, create new medical treatment procedures, and manage chronic illnesses. Though ML has improved significantly, models still suffer from adversarial examples, which present a special case of the broader problem of unexplained and overconfident behavior of ML models outside the training distribution. Vulnerabilities in advanced technologies ML systems have been exposed thanks to the discovery of adversarial examples [6-8]. An adversarial example is data that has been carefully crafted to fool machine learning models. Undoubtedly, there has been ample traction gained for adversarial ML within health care due to the very potential limitations availed by the existing ML models. For example, an adversary may provide fresh covert data to a healthcare ML model so that it misclassifies a patient with hypothyroidism. Among several other reports documenting recurrent/adversarial attacks on ML models in medical healthcare image processing are those who aim to distort the finding-through sound addition-based alterations, for example, misclassifying a benign mole as cancerous. On the other hand, the healthcare sector has quickly advanced ML-based systems, which have upgraded their capabilities for improving disease detection and patient care. The chapter writes this overall class that fits many of the defense strategies pernicious of adversarial machine learning based real-time monitoring for vital signs.

2.2. Extensive Analysis of Healthcare Machine Learning-Based Systems

Abnormal vital signs frequently predict patient progression and unpleasant outcomes [1, 2]. These symptoms often manifest anywhere from a few hours to a few days before the occurrence, giving people a window of opportunity to take preventative action [3]. Considering this Early Warning Systems (EWS) for clinical decision support was created [4]. These systems use routine monitoring of vital signs in conjunction with a set of specified criteria or a cut-off range to notify doctors when a patient's condition worsens. Observing vital signs such as peripheral oxygen saturation (SpO2), respiration rate (RR), blood pressure (BP), heart rate (HR), core body temperature (core BT), and sometimes awareness state are the most common parameters used in EWS [5]. Multiple vital signs and other patient data are aggregated into one weighted EWS, and these criteria are all explicitly articulated. Each of these signs is given a weight based on a predetermined cutoff, and a total risk score is then determined by putting all of the weighted values together [6]. The Modified Early Warning Score (MEWS) [7], the National Early Warning Score (NEWS) [8], and the Hamilton Early Warning Score [9] are all aggregate weighted EWS used to predict cardiorespiratory insufficiency and mortality; they all include health parameters and cognitive performance (Alert, Verbal, Pain, Unresponsive [AVPU]), but they all have different limits for evaluating performance.

Limitations in predicting power are present in weighted EWS aggregate. Initially the results, only reflect the patient's current risk without including trends or providing data pertaining to the prospective a path fraught with danger [9]; hence, the ratings do not convey the extent to which the patient is gaining ground or worsening as well as the pace of this change [10]. Second, because the score for each parameter is generated separately, the scores do not reflect any relationships between the parameters [6]. (e.g., depending on the individual, the significance of a given HR or RR reading might change when core body temperature is considered). Modern EWS methods use machine learning (ML). Machine learning (ML) models eliminate the need for predetermined rules by instead figuring out these patterns and correlations on their own [11].

ML models are computationally costly, but they have advantages over aggregate weighted EWS, including the ability to integrate patterns in risk ratings, compensate for a wide range of a medical variables, and tailor recommendations to specific populations and treatment settings [12]. ML models, like other EWS, may be embedded into EHRs to continually evaluate vital sign readings and offer outcome predictions among other components of a medical decision-making system [13]. ML models' capacity to predict medical worsening in patients who are adults based on vital signs was examined in two recent systematic studies [8, 14].

Only two retrospective studies fulfilled the inclusion criteria of Ghosh et al. [15] evaluation of the usefulness intriguing patterns in non-constant vital signs data individuals above the age of 18 admitted to any hospital department (HD). Vital sign trends were shown to be useful in identifying clinical worsening, but the study also stated that there is a dearth of research on sporadically observed trends in vital signs and emphasized the necessity of clinical trials. Gokhale et al. [16] did a review contrasting the efficiency of aggregate-weighted EWS with that of ML-based EWS with regards to both accuracy and effort. Six research studies were found that published the measures for the efficiency of both the EWS and ML-based and the aggregate-weighted EWS, and the analysis was limited to studies reporting transfers of adult patients to ICUs or death as the outcomes. According to the findings of the review, ML modeling outperformed aggregate weighted models whenever clinical burden was being generated. Also, they stressed the need of defining degradation outcomes consistently and using defined performance signs. These are crucial findings, but there hasn't been a comprehensive analysis of the research on ML-based EWS that considers the frequency with which vital signs are measured, the type of care provided, or the clinical outcomes achieved to identify limits of present methods and emerging tendencies in research and recommend avenues for future study. The goal of this study was to systematically analyze the literature on ML-based EWS that use data from vital signs to predict the likelihood of physiological deterioration in both inpatient and outpatient populations. When one category has much fewer or more samples than another, the dataset is said to be imbalanced.

Several studies were undertaken in different hospital settings, whereas Gokhale et al. [16] looked at patients in the community. While three research [5–7] sought to create a Residence-Based Supervision Equipment, the vital signs data utilized came from the Medical Information Mart for Intensive Care (MIMIC and MIMIC-II) databases [8,9], which compile information from patient monitors in various intensive care units. Five studies [8,10-13] took place on wards with general, four research [14,16-18] were conducted in emergency departments; seven studies [14, 17,19,20-23] were conducted in intensive care units; two studies [15,21] were carried out in recovery wards; and four research [8,11,13,14] were conducted within the context of acute care wards (step-down units, medical admission unit). The research included as little as 12 patients in their cohorts [19] and as many as 10,967,518 patients in their cohorts; [20] all are incorporated in Table 1.

Table 1. Prediction algorithms and comparisons based on machine learning (ML)

Ref.	The samples include	Quantity of occurrences	Modelling using Machine Learning (s)	Problems with Missing Data	Characteristics of the Top ML Model	comparisons between ML models	Forecasting time frame
[1]	Over 35,000 people were accepted.	199 cardiac arrests; 1161 unplanned ICU hospitalizations; 1789 fatalities; 3149 any outcome	The Use of a Decision Tree	Generally Unknown	AUROC=0.708 for cardiac arrest prediction; ICU admission (ICU)	Generally Unknown	During the past twenty-four-hour period
[2]	Eighteen hundred and eighty patients (1971 admissions)	The percentage of patients who had a CRIe episode was 53.6%, or 997 out of a total of 1056 patients admitted.	Classification method based on a variant of the random forest with non-random splits	Generally Unknown	Random forest AUCs were stable at 0.58 and 0.60 before rising from 0.57 to 0.89.	Recovery yielded an AUC of 0.7 with logistic regression and 0.82 with lasso logistic regression	Prior to the start of the event and within 4 hours of it
[3]	214 individuals	Outcome was achieved in 40	k-nearest neighbour	Generally Unknown	F1 score=0.50, AUPRC=0.35,	F1=0.10, AUPRC=0.10,	The 30 days before to the event.

		individuals (18.7 %).	(KNN), Support vector machine (SVM), random forest (RF), gradient boosting (GB) and adaptive boosting (AB),		precision (PPVg)=0.62, and recall=0.50 were all used to predict death within 30 days due to sepsis using gradient boosting.	PPV=0.33, recall=0.6 for k-nearest neighbor; F1=0.35 for random forest; F1=0.27 for adaptive boosting; F1=0.40 for PPV=0.43, recall=0.38 for SVM; F1=0.43 for Adaptive Boosting, AUPRC=0.31, PPV=0.43, recall=0.38.	
[4]	Major heart surgery patients who were categorized by risk (n=13,631)	For every 100 patients admitted to the intensive care unit, 499 will be readmitted unexpectedly, for a total of 578 (4.2%) successful outcomes and 3.66%) readmissions.	Logistic regression	Missing-value observations were omitted.	24 hours before the occurrence, logistic regression predicted it. 12 hours ahead: AUROC=0.815; 6 hours ahead: AUROC=0.841	Generally Unknown	Approximately 24, 12, and 6 hours before the start of the event
[5]	Number of Registrants: 269,000	The number of results is 16,452. (6.09 percent)	Two types of statistical analysis are often used: univariate and bivariate.	Median value imputation, and forward imputation	slope improved AUC by 0.014, Trends increased model accuracy (AUC 0.74 vs. 0.75)	Generally Unknown	Within the prior four hours
[6]	Two hundred patients recovering after surgery for oesophageal or gastric cancer	Generally Unknown	Kernel estimation, one-class support vector machines, Gaussian processes, and classifiers	When a channel isn't present, its average is substituted.	AUC=0.26, Accuracy=0.94, partial specificity=0.92, sensitivity=0.95	Gaussian mixture models: 0.90, specificity=0.84 sensitivity=0.97, partial AUC=0.24; Gaussian processes: 0.90, specificity=0.89; sensitivity=0.91, partial AUC=0.26, kernel density estimate: 0.91, specificity=0.87, sensitivity=0.94, partial AUC=0.26.	Generally Unknown
[7]	Resulting in 22,853 Intensive Care Unit Admissions	11.28 percent, or 2577 inpatient stays, include patients with proven sepsis.	Analytical classifier	Imputation results are carried over.	AUROC for sepsis at start is 0.888, APRl is 0.60, and accuracy is 0.80; for sepsis 4 hours before start, AUROC is 0.74, APRl is 0.28, and accuracy is 0.57.	Not specified	At the time of the event's start and during the previous 4 hours
[8]	There were 85 individuals.	Generally Unknown	J48 Analyze classifier output using random tree, decision tree, and sequential minimum optimization (SMO, simplified SVM).	If 1 vital sign is absent but others are clean, assume recoverability and median-pass and k-nearest-neighbour imputation.	The 24 classifier combinations' Hamming scores varied from 90% to 95%, with an F1-micro average of 70% to 84% and accuracy between 60% and 77%.	Generally Unknown	The immediate prior hour

[9]	There were 4893 individuals.	Generally Unknown	MapReduce random forest, sequential minimum optimization, random forest, and the J48 decision tree	We don't save data that has gaps that are too close together over a lengthy time frame.	For 60-minute, 90-minute, and 120-minute prediction horizons, random forest earned F scores of 0.96, 95.86%, 0.95, 95.35%, and 0.95, 95.18%.	Within a 60-minute forecast horizon, the J48 decision tree F score is 0.93 with an accuracy of 92.46, 0.92 with an accuracy of 91.59, and 0.91 with an accuracy of 91.30; Event prediction using sequential minimum optimization: Within 60 minutes, F=0.91 with 90.72 accuracy; within	An Hour before the show
[10]	There were 297 people who were accepted.	A total of 127 individuals (43% of the total) had at least one clinically significant CRI incident while in the step-down setting.	TITAp rules, a rule fusion approach, and a rule-based feature-to-random forest classifier-learned prediction model.	Generally Unknown	Seventeen to fifty-one seconds after CRI start (inaccurate alarm every twelve hours); ten to fifty-eight seconds.	eleven seconds, twenty-five seconds before CRI (false alarm each twelve hours); five minutes, fifty-two seconds prior (event prediction) (false alarm each 24 hours).	Prior to the commencement of CRI, between 17 minutes and 51 seconds
[11]	total no. of 763 individuals	There were 197 individuals who had a cardiac arrest incident (25.8 percent).	Transfer learning modelling (TTL-Reg)	Similar-age and-gender median imputations	The AUC for predicting events with TTL-Reg is 0.63.	Generally Unknown	Earlier than 6 hours before the start time
[12]	Attendance at the Emergency Department for Reasons Other Than Emergencies	There were 374,605 visits to the ED out of 233,763 patients who were eligible; 1097 (0.3%) individuals had a cardiac arrest.	ANNq with MLP, ANN with LSTMr, and hybrid ANN vs. random forest with logistic regression	Generally Unknown	Multilayer perceptron, LSTM, and hybrid ANN all have AUROCs of 0.929 for event prediction.	The area under the receiver operating characteristic curve for a random forest is 0.923%, while for a logistic regression, it is 0.914%.	Within the prior twenty-four
[13]	total no. of 52,131 individuals	There were 419 cases of cardiac arrest (0.8%); 814 unattempt Ed fatalities (1.56%).	RNNs with three LSTM layers handle data from time series better than logistic regression and random forest.	When no recent data was available, the median value was used instead.	Recurrent Neural Networks for Event Prediction: AUROC=0.85, AUPRCt=0.044	logistic regression AUPRC 0.007, AUROC 0.613 Random forest AUPRC 0.014; AUROC 0.78	30-240 hours before the big day
[14]	Seven hundred and two individuals with non-traumatic chest discomfort with no clear cause	Primary result was achieved in 29 participants (4.13%).	Random forest was used in an ensemble learning-based framework to choose independent variables.	Generally Unknown	The predictive ensemble learning model has AUC=0.812, cut-off specificity=63.4 %, score=43, and sensitivity=82.8 %.	Generally Unknown	Come to the ED within 72 hours.
[15]	total no. of 2809 individuals	Instances of tachycardia, n = 787	Random forest classifiers with regularized logistic regression	Heart rate and respiration rate data gaps were filled using discrete Fourier transform and cubic-spline interpolation.	Random forest for event prediction: AUC=0.869, accuracy=0.806	Using L1 regularization for a logistic regression, we get an AUC of 0.8284 and an accuracy of 0.7668.	Within the prior three hours

[16]	There were 90,353 patients in UCSFw and 21,604 in MIMICx-III.	1179 instances of sepsis (1.3%), 349 cases of severe sepsis (0.39%), and 614 cases of septic shock (0.68%) at UCSF; 1.91%, 2.82%, and 3.82% at MIMIC-III (4.36 percent)	transfer learning using MIMIC-III as source and Gradient tree boosting UCSF as destination.	Imputation results are carried over.	We could identify sepsis with an AUROC of 0.92, severe sepsis with 0.87, septic shock with 0.96, and severe sepsis prediction with 0.85.	Generally Unknown	As early as severe sepsis or sepsis symptoms manifest; within four hours of developing server sepsis or sepsis.
[17]	total no. of 178 individuals	160 patients (89.9%) had at least one microevent during admission; 116 (65.2%) had one lasting more than 15 minutes.	Classification using Random Forest	Generally Unknown	RF accuracy=92.2%, specificity=93%, AUROC=96.9%, sensitivity=90.6 %	Generally Unknown	Generally Unknown
[18]	Patients undergoing a variety of unplanned treatments	Cases of sepsis: 242	The Logistic Elastic Net Classifier	When several measurements were available, the median was used; otherwise, earlier values were preserved (sample-and-hold extrapolation); mean imputation filled gaps.	An elastic net logistic classifier trained with only entropy features had an AUROC of 0.67 (accuracy 47%), one trained with social demographics and EMR features had an AUROC of 0.7 (accuracy 50%), and one trained with all features produced an AUROC of 0.78 (accuracy 61%)	Generally Unknown	Within 4 hours of start
[19]	total no. of 2995 individuals	There were 343 cases of sepsis (11.5%) among patients.	Random dropout prevents overfitting in CNN (raw patient data pictures) and multilayer perceptron.	Generally Unknown	CNN classifies events with 86.1% accuracy using minute-by-minute observations and 78.2% accuracy using 10-minute sample intervals.	One-minute observation frequency: multilayer perceptron, 76% accuracy; ten-minute observation frequency: 71% accuracy.	Generally Unknown
[20]	PACU, Rigs Hospitalet, Copenhagen University	Bedside monitors (IntelliJ Vue MP5, BMEYE Nexfin) used for postoperative patients admitted to the intensive care unit	We have 178 individuals.	160 patients (89.9%) had at least one microevent on admission, and 116 (65.2%) did so afterwards. lasting more than 15 minutes.	Create a model to predict PACU patient outcomes using real-time cardiopulmonary vital indicators.	SpO2, MAP, ASD, SBP and HR	Continuous monitoring of vital signs (SpO2, BP, and HR) every minute and recording of results every 15 (MAP) and ASD every 10 hours
[21]	Care for adults in the intensive care unit	Bed master system intensive care unit bedside monitors; continuous monitoring for up to 24 hours	Patients undergoing a variety of unplanned treatments	Cases of sepsis: 242	Vital signs may predict sepsis within 4 hours.	HR, ASD, MAP, SBP, DBP, SpO2, RR, temperature, gender, weight, race, comorbidities, admission unit, surgical specialty, wound kind,	1 reading per hour
[22]	John Radcliffe Hospital's general wards in Oxford, England	Continuous patient monitoring for at least one full day	150 inpatients on the g.i.	Generally Unknown	Check your heart rate, respiration rate, oxygen saturation, skin	Respiration rate, HR, SPO2, Temp, standard/diastolic blood pressure	Five seconds every thirty minutes (BP) (other vitals)

					temperature, and blood pressure averages.		
[23]	Tennessee's Methodist LeBonheur Medical Center in Memphis	Cerner CareAware iBus, a system of bedside monitors,	We have 2995 individuals.	There were 343 cases of sepsis (11.5%) among patients.	Divide person into non-sepsis & sepsis groups using data within 12 hours of admission.	Heart rate, mean arterial pressure, diastolic and systolic BP, SPo2, age, race, gender, and blood oxygen percent change.	60 Seconds

i. Comparative Analysis of Aggregate-Weighted EWS

A total of nine investigations evaluated the efficacy of ML-based EWS as compared to total-weighted EWS. The NEWS [2,5], MEWS [2,5,6,16], and the TIMI score, [16] were all been compared in studies examining cardiorespiratory consequences, physiological decline, or death. SIRS criteria, qSOFA, and SOFA, as well as Acute physiology score (II) simplified, were all used in the three studies examining sepsis-related outcomes [8,12]. The Acuity and Korean Triage Score [1], the Model of Sepsis in the Singapore Emergency Department [12], and the post anesthesia care unit alert system are just a few examples of regionally or locally specific scoring systems that have been compared in a few studies.

ML models outperformed total weighted EWS systems for every clinical result in all 9 experiments apart from a heart attack in the research of Bojanova et al [11]. For instance, Chi et al. [13] found that an LSTM-based neural network outperformed MEWS (AUROC = 0.886) on the same dataset, with an LSTM-based network achieving an AUROC = 0.933. Hackmann et al. [17] found that recurrent neural networks outperformed MEWS (0.603) and the KTA Score (0.785) with an AUROC of 0.85. Badriyah et al. [18] observed substantially smaller gains, with logistic regression producing an AUROC of 0.779 compared to MEWS's 0.754 for the same 24-hour prediction window.

This scoping study reveals that ML-based EWS models have a great deal of potential, but that more work needs to be done before they can be successfully deployed in clinical practice.

ii. Forecasting Timeframe

The time frame during which a model may reliably foretell the occurrence of a negative outcome is known as the prediction window. Our study found that most studies predicted clinical worsening anywhere from 30 minutes [16] to 72 hours [16] in advance. Too short of a prediction window is unable to provide a positive effect on patient health (it will not provide a medical staff enough time to assist), while too long of a prediction window has been shown to decrease model performance in many studies [17,19, 21,23] (e.g., The AUROC decreases from 0.88 at event beginning to 0.74 four hours beforehand). Instead of focusing only on optimizing a model performance parameter like AUROC, prospective studies of ML EWS aim to strike a compromise among a medically meaningful prediction window and clinically acceptable model performance.

iii. Clinically Implementable Considerations

This evaluation includes studies on the building of ML models; However, it does not specify the manner in which the results will be conveyed to medical practitioners. Due to the opacity of several ML models [16,17], doctors may not know the cause of an alert until they examine the patient, which might cause delays in time-sensitive situations. Explainable ML approaches have recently advanced, and the medical community and regulators may embrace them [18,19]. Several explanation techniques may currently describe the decision-making process of convolutional neural networks [15]. Other explain ability algorithms are model agnostic; therefore, they may be employed with any model [20]. Chiu et al. [22] created an explainable EWS on top of a temporal convolutional network with its own explanation module. While both techniques show potential, EWS has seen limited use. The objective evaluation of explanation strategies' efficacy is a complex, ongoing problem, but ML-based EWS research is vital for clinical use [23].

iv. Enhanced Study Environments

The vast majority of the listed research took place in hospital wards. In addition to their usefulness in the hospital environment, EWS have a sizable clientele in the outpatient sector, especially after patients have been released. Specifically, 1.8% die in 30 days following surgery, as shown by the VISION research [8]. Three to four weeks [8] after surgery, patients seldom see their surgeon again for postoperative follow-up. It has been found that many patients have significant postoperative complications such as hypoxemia [14] and hypotension [16] that go unnoticed for an extended length of time during this time. Most EWS research has been carried out in hospitals because of the abundance of continuous vital signs data, but advances in wearables and remote monitoring present an option to shift the focus of EWS studies to outpatient care facility, where there is a pressing need for clinical trials.

v. Evaluation retrospective versus prospective

It is possible that the effectiveness of an algorithm in a situation could be poorer than that attained in a well-planned look back scenario [8], since all but one of the studies combined into a single behavior. However, it is not known how frequently Such EWS might identify signs of clinical decline that was hardly previously observed by medical staff. In addition, Doctors may disregard indicators of clinical worsening, even when the likelihood of degradation has been precisely determined [13] due to alert fatigue. A prospective study of an ML-based EWS by Tarassenko et al. [21] demonstrated that in contrast with preexisting combinational-weighted-alarm-system, RF classifier reduced error levels by eighty-five percent and the omitted alarm by warnings was 73%. Although 2 physician experts assessed the severity of the forecasts separately, no further research was done to analyze the clinical significance of these warnings, leaving the topic of therapeutic value unresolved. Prospective assessment of model correctness (as a means of assessing quality of the model changed when presented using actual patient records) and measurements of health outcomes is an important next step for ML-based EWS research (an effort to learn if warnings really have clinical advantages) [129-130].

vi. Performance Measurement Standardization

One major takeaway from this synthesis is the absence of a universally accepted norm for reporting performance metrics across studies within the scientific community. In cases there is duplication, it is unclear if most applicable to clinical practice measurements were used, making meaningful comparisons between the results of these studies problematic. It is typical in the ML literature for the AUROC to serve as the primary performance parameter reported in the research reviewed here. However, it has been suggested that AUROC is insufficient for gauging the EWS's efficacy in a clinical situation [17].

According to Churpek et al. [20], the incidence of physiological decline may be less than 0.02 per day in a typical inpatient context, although this information is not included into AUROC. As a result, AUROC may be a deceptive indicator that causes clinicians to overestimate therapeutic benefit while underestimating clinical burden and resources. [18] It is possible that too even a very sensitive and selective model will never result in conclusive evidence for a favorable outcome after testing when the prevalence is low (0.1) [14]. As a result, it is preferable to use metrics for reporting purposes that consider the frequency of occurrence.

Early result detection vs. issuing fewer false-positive warnings to reduce alarm fatigue [22] are two aims that affect the performance of an EWS. The proportion of correct predictions made in a given time frame may be used as an indicator of sensitivity, making it a useful statistic for judging progress toward the first objective. There is a high degree of confidence in the results, which accounts for good predictive value, and it could be utilized to assess the detrimental effects of false-positive alarms on patient care since it provides a proportion of successful therapeutic interventions. The number of patients that require further evaluation to discover one outcome may be a helpful metric of the clinical value and cost-efficiency of each warning. The clinical value of the EWS may be shown by all these parameters for examine balancing result detection with workload [18]. The F1 score is the arithmetic average of the recall and accuracy scores and is also a helpful value because it reveals how accurate the model is as a whole (sensitivity). A deeper evaluation of the algorithm's effectiveness may result from a more even weighting of the two indicators [18].

vii. Compared to the "Reference Standard" EWS

In a similar manner, only 9 of the research we reviewed compared their "gold standard" aggregate-weighted EWS, such as NEWS or MEWS, using machine learning. In order to more accurately compare different EWS models, it would be helpful to have a frequently used aggregate weighted EWS reported in future studies. Considering that all of NEWS's input variables can be monitored automatically and in real time by devices, it might prove to be an invaluable tool in this line of investigation [130-131].

viii. The review's strengths

The search was exhaustive without being too narrow in its emphasis on clinical outcomes, sample sizes, or time constraints. This made it easy to include as many papers as possible. Our search method was thorough since no further studies were found via citation monitoring following the first search. The review's inclusion criteria allowed for the comparison of results from studies performed in different clinical settings, such as ambulatory care and specialized units or wards, which had not been done in earlier reviews. This aided in describing application of prediction models based on ML in a variety of healthcare settings, each with their own unique clinical outcomes. Data from the original research was used to evaluate how well the ML models analyzed compared to the aggregate weighted EWS. This demonstrates the variation in the models' ability to predict clinical deterioration [132].

ix. The review's limitations

There are some restrictions with what these results can do. All evidence in the scoping review consisted of published findings which may have changed the outcomes by omitting relevant unpublished information. In addition, differences in patient characteristics, kinds of treatments and research methods can make the findings less generally applicable. In different studies, selecting a clinical outcome was not standardized, some using varied criteria or mixes of EWS and others including from a single measurement to several vital sign recordings. Because there were so many machine learning techniques, different time periods for making predictions and ways to report results, it was not sensible to combine the studies for analysis [133].

2.3. Artificial Intelligence (AI) Approaches for Autism Spectrum Disorder (ASD) Assessment in Healthcare

In this section, we will delve into AI Approaches for Autism Spectrum Disorder (ASD) Assessment in Healthcare, which addresses one of the most challenging and difficult issues faced by caregivers and families dealing with autistic children. The integration of Internet of Things (IoT) systems has garnered significant curiosity recently, particularly in the realm of ASD treatment and diagnosis. Despite numerous publications focusing on ASD, there remains a scarcity of studies that comprehensively explore ASD from an AI perspective [135-136].

Aldahiri et al. [8] examined problems in a variety of smart devices, sensors, and systems linked to health difficulties, which are directly relevant to our research. As per [7], the Internet of Things (IoT) has surfaced as a contemporary information technology. Storing the information gathered from monitoring physiological characteristics like heart rate is one of the most intriguing applications for the increasing number of wearable sensors in the medical field. The main elements of this technology are wireless body area network (WBAN), cloud computing, and the Internet of Things (IoT). The efficacy of IoT-powered wireless "SS networks" depends on machine learning techniques since a lot of data has to be intelligently handled [137].

As Zhang et al. [9] illustrate, amnesia is a symptom shared by individuals with Alzheimer's disease and dementia as well as youngsters with autism spectrum disorder. Consequently, people are more prone to face perilous situations, such escaping their houses. Meanwhile, this device lets autistic kids stay put, which is a huge relief for them. To solve these issues, the Alzimio platform was developed, which is based on Internet of Things devices. Medical personnel may see their patients' precise whereabouts on their cellphones thanks to a system created by [10] AlSkaif et al. [10]. Patients who have left their comfort zones may find these methods very helpful.

Bojanova et al. [11] used data mining techniques such as regression, clustering, and classification to make early diagnoses of ASD. The provision of suitable education and assistance to patients and their careers depends on the early identification of ASD. According to their findings, classification algorithms provide the most precise diagnosis.

Chen et al. [12] investigated how therapies for autism affect appropriate behavior using data mining techniques. Using this strategy, we may better understand and anticipate the needs of children with autism. They were able to differentiate between appropriate and inappropriate actions based on these strategies.

Chi et al. [13] examined forty-five articles that addressed ASD using supervised machine learning and classification methods. The models that were most often used were; SVM, Decision Trees, Random Forest, LASSO, Neutral Network, regression, Conditional Forest, Naive Bayes, ENet, Random Tree, and Flex Tree. In their investigation, Koumpouros and colleagues surveyed 83 papers that were published after the year 2000. The articles vowed to use computing power and wearable technologies to intervene while dealing with autism spectrum disorders. [14].

The Robota robot toy, used in Ghosh et al. [15] to showcase the possibilities of the AuRoRA project, may be helpful for autistic children. Three autistic children's progress was examined using an assessment tool called Conversation Analysis (CA). This led them to the conclusion that the children are really communicating with the grown-up robot. The research characterized shared attention in autistic children and emphasized computer and robot treatment for ASD [137-138].

For each study, a thorough examination of both internal and external factors was conducted to establish a connection between the technical aspects of the Systematic Literature Review (SLR) method and its use in ASD methods. Subsequently, these queries were used to carry out the research investigation.

a. Which methodologies pertaining to autism spectrum disorder are being examined and evaluated in this analysis?
b. What methods and procedures are used in the management of autism spectrum disorder?
c. What are the performance metrics for ASD?
d. ASD approaches use several platforms and sensors.?

i. ASD approaches

People with autism have to cope with the disorder every day of their life since it is not treatable. It is much easier to put the therapeutic treatments into motion quickly if you can identify when they are needed. Research on ASD is given considerable weight in this section. In order to enhance ways to treating ASD, the papers should be researched further. Figure 4 shows that our research methodology had two parts: methods for diagnosing and evaluating the severity of autism spectrum disorder (ASD) in children, and programs to improve the quality of life for these children. Feature selection, data mining, virtual reality, object-oriented, genetic algorithms, reporting on DL, peer-to-peer (P2P) and electroencephalography (EEG) were some of the methods utilized in subsequent investigations to accomplish these goals [139-140].

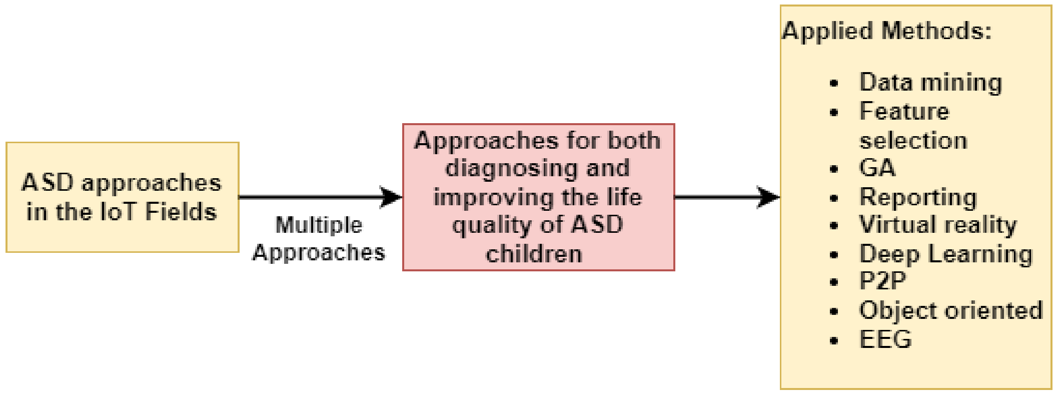


Figure 4. Presented taxonomy for the ASD approaches.

ii. *Individual with ASD may be diagnosed, and their condition severity measured using a variety of different methods.*

Two of the most challenging aspects of ASD are forecasting and monitoring. A person with autism may see the world differently, which may have an effect on the health care and education systems. The Internet of Things (IoT) has accelerated the process of diagnosing and treating pediatric illnesses, both minor and severe [141].

This improvement in health and education services would help the people. The assessment factors that were investigated, the basic idea, the applied approach, the platforms, and the sensors are all shown in Table 2.

Badriyah et al. [18] put up a system for autonomous health monitoring based on wearable sensors that can detect brainwaves. On a frequent basis, those who care for autistic people were apprised of their loved ones' development. By tracking electrical activity in the brain, sensors may alert doctors and employers when a patient's condition is critical. Brain data improves sickness prediction.

Wearable technology established on social sensing, blending privacy audio features, environment sensing, and behavior monitoring was introduced by Chen et al. [19]. The platform for monitoring well-being designed audio privacy wellness features to assess information and voice quality without saving raw audio data. They built an app that demonstrates the long-term link between physical and psychological data using Android devices and servers. It's all part of their case study.

It may also be tested in clinical studies on real people. Additionally, an Internet of Things (IoT) system for tracking critical patient parameters and health events was introduced by Churpek et al. [20]. A smartphone or other gadget sends this data to a server in the cloud. By combining the user's recorded metrics—including heart rate, oxygen saturation percentage, and body temperature—with cloud computing, we can ascertain the user's health state. Data collected from a user's mobile device may be shown on a pre-programmed computer or mobile device [142].

In order to aid autistic people, Chiew et al. [21] created a Service-Oriented Architecture (SOA). It is possible to track the physiological status of autistic people and their surroundings with the help of the suggested wearable sensors. For the benefit of elderly and disabled patients in the comfort of their own homes, Chiu et al. [22] created an Internet of Things (IoT) therapeutic system using cheap and easily available gadgets like mobile, cameras, and other wireless goods. They helped create a more health-conscious family by treating patients using image processing and integrated computers. The writers laid forth the importance of accuracy and cognitive theory. This treatment has the potential to improve facial expression for those with autism spectrum disorder (ASD) and Parkinson's disease. Clifton et al. [23] documented some of the behaviors and responses of autistic individuals, including changes in voice pitch, non-verbal communication, and complicated tactics.

Table 2. A comparison of the approaches used for diagnosing and monitoring the degree of illness with autism spectrum disorder (ASD).

Ref.	**Key Points**	**Method**		**Characteristics of evaluation**		
			Time	**Specificity**	**Accuracy**	**Sensitivity**
[18].	using brain signals to focus attention on one's health using SS network	Data Mining	✓	✗	✓	✗
[19].	Long-term use of wearable technologies to evaluate psychological health	Reporting	✓	✗	✓	✗
[20].	Using IoT to monitor healthcare	Feature Selection	✗	✗	✓	✗
[21].	Avoid obtaining injured by autistic people who aren't at responsibility.	Genetic algorithm	✗	✗	✓	✗
[22].	Emotional and visual indicators in a smart home	DL	✗	✗	✓	✗
[23].	Recognize the emotions of children with autism	DL	✗	✓	✓	✗
[24].	Monitoring the actions of an autistic person might be quite risky.	Feature Selection	✓	✗	✓	✗

[25].	Autism condition can be detected early if it is recognized using SS network.	Feature Selection	✓	✓	✓	✓
[26].	Autism children's situation can be properly appreciated with virtual reality therapy.	Virtual reality	✓	✗	✗	✗
[27].	A reliable strategy for the early detection of autistic spectrum disorders in youngsters	Feature selection	✓	✓	✓	✓
[28].	A framework for detecting autism in children using SS network	Data mining	✗	✓	✓	✓
[29].	ML-based ASD detection	Feature selection	✓	✗	✗	✗
[30].	Autism spectrum disorder assessment in children using SS network	Data Mining	✓	✗	✓	✗
[31].	IoT sensors detect autism-related special needs in youngsters.	Data Mining	✓	✗	✗	✗
[32].	Providing instructors of autistic children with the greatest possible feedback	Data Mining	✓	✗	✓	✗
[33].	Removing the autistic learner from reliance on others' help and support	Data Mining	✓	✗	✓	✗
[34].	ASD's ability to recognise and express emotion	Data Mining	✗	✗	✓	✗
[35].	Acknowledging the necessity of ASD via PECS	Data Mining	✓	✗	✗	✗
[36].	Using robots to train autistic children and enhance their talents using SS network	Genetic algorithm	✓	✗	✓	✗
[37].	The recommended technological treatment for ADD/ADHD in parents using SS network	Reporting	✓	✗	✓	✗
[38].	Investigating the ways in which intelligent items assist autistic individuals	Feature selection	✓	✗	✗	✗
[39].	Intelligent technology has enabled autistic children to perform previously inaccessible tasks.	Object- oriented	✗	✗	✓	✗
[40].	In order to improve the autistic patient's heuristic detection issue,	P2P	✓	✗	✗	✓
[41].	Students' social and communication skills will be improved thanks to the robot Kasper to detect ASD.	P2P	✓	✗	✗	✗
[42].	To assess the effectiveness of human and robot-based treatment for children with autism spectrum disorder (ASD).	Reporting	✗	✗	✗	✗

[43].	To develop an IoT-based assistive device for people with autism spectrum disorder (ASD).	Reporting	✓	✗	✓	✓

Technical and comparative analyses of current ASD methods are presented here. Some technical and statistical replies to the problems posed in Section 2.3 were as follows:

a. *Which methodologies pertaining to autism spectrum disorder are being examined and evaluated in this analysis?*

The fraction of existing therapy options for ASD is shown in Fig. 5. Improving the lives of children on the autism spectrum seems to be the primary emphasis of most publications. For the purpose of autism diagnosis, this approach has been used in sixteen investigations. In contrast, twelve articles covered every conceivable way of diagnosing and grading the seriousness of disease. Since there is currently no cure for autism, there is an enormous incentive to keep researching methods to make life better for those with the disorder.

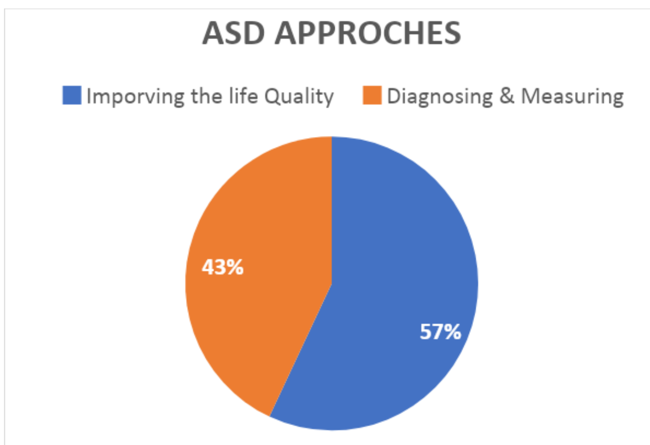


Figure 5. Variety of ASD treatment methods in the published literature

Furthermore, at the earliest age of 3, parents or caregivers recognize autism and its severity and offer treatment solutions. Although there are numerous benefits to early autism detection [143].

b. *What methods and procedures are used in the management of autism spectrum disorder?*

Figure 6 shows that data mining techniques are the most common. The figure is divided into two axes: the y-axis shows the number of papers, and the x-axis shows the various methodologies employed in ASD. One of the main ways to obtain insightful information from huge datasets is to employ pattern-recognition algorithms. Effective early detection approaches and other clinical services technologies pertaining to diagnostic and medical data have been generated by data mining and the healthcare industry. Generalization, classification, characterization, grouping, evolution, data visualization, association, pattern matching, and metarule guided extraction are all methods that fall under the umbrella of mining. Children on the autistic spectrum (ASD) are most often helped by data mining technology, according to this research. Wearable sensors and other smart devices that gather data are required for its usage. It should be noted that there are insufficient intelligence techniques in such technology. Instead of using it in the real world, it is employed in a controlled environment [144-145].

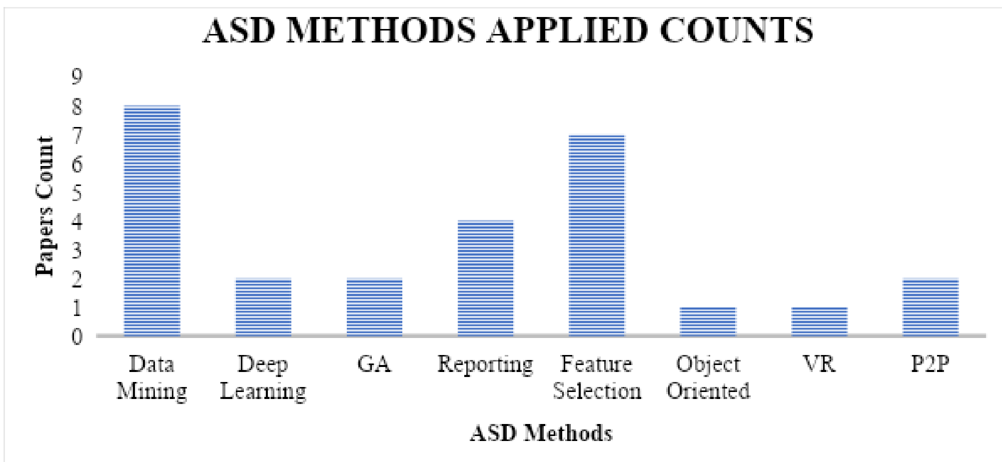


Figure 6. The Inclusion Rate of Procedures in ASD Approaches within Publications.

The two most common methods for selecting features and reporting on them are covered in this paper. Feature selection techniques, like GA, or other methods may be used to choose a subset of the features input variables, allowing dimensionality to be minimized. The approaches utilized in the reporting were derived from papers that explored the use of robots to enhance patients' quality of life. Its purpose is to evaluate the perceived differences between human and machine care. You may consider them as an alternative because of their sufficient speed, but they still need further improvement.

Furthermore, GA, P2P and DL methods that provide a range of AI-powered services to ASD persons have been highlighted in recent articles. The methods are quick enough, but not precise enough, to be of any value in parallel computations carried out by Internet of Things devices.

c. *What are the performance metrics for ASD?*

As shown in Figure 7, the research publications were evaluated according to a number of quality criteria related to ASD methods, including sensitivity, accuracy, response time, and specificity. The most essential feature elements of autism spectrum disorder detection devices and systems based on the Internet of Things, according to our results, were response speed and efficiency. We spoke about four main processes and elements on the x-axis, but additional important things like CCR, dependability, processing speed, etc., might be looked at on the y-axis according to their numbers.

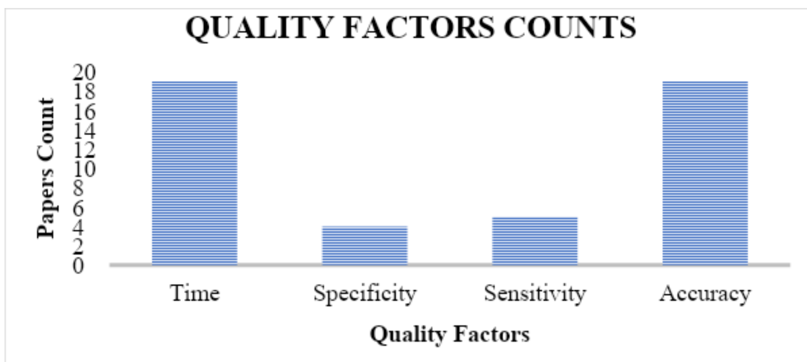


Figure 7. Comparative Analysis of Quality Elements in ASD Approaches.

d. *ASD approaches use several platforms and sensors.?*

The number of research projects that employ ASD concepts with different platforms and sensors is depicted in Figure 8. These days, "wearable sensors" comprise a variety of sensors and technologies, such as pulse oximetry, heart rate variability (HRV), and smart belts. The ASD technique comparison across platforms and sensors is shown in the pie chart.

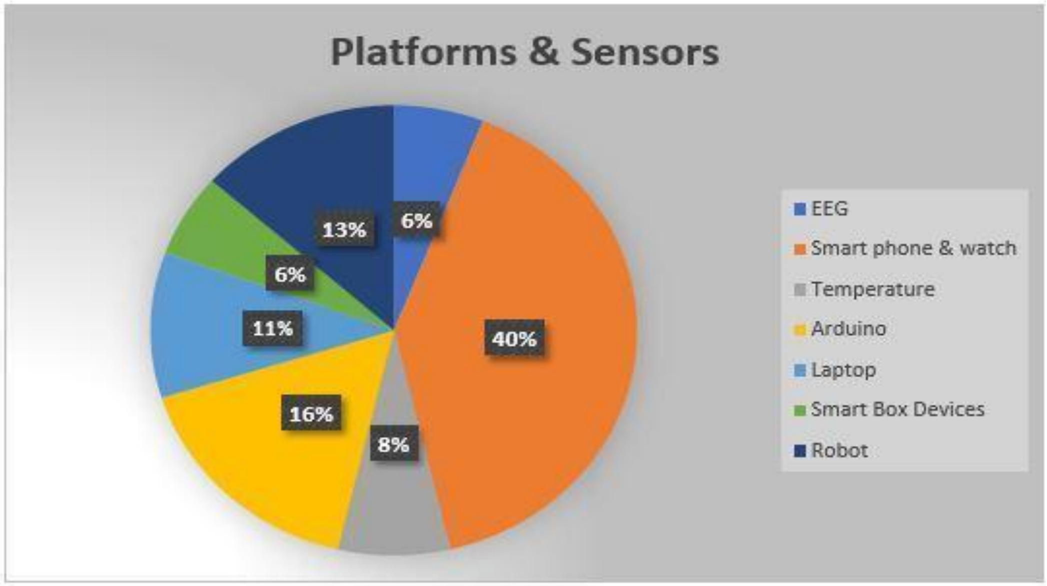


Figure 8. Analyzing Sensor and Platform Variations in ASD Techniques.

iii. Unresolved problems

Several issues and perspectives remain unaddressed in the current literature about the development of Internet of Things (IoT) methods for children with ASD. What follows is a list of some of the unanswered questions:

- When it comes to identifying and assessing the severity of illness for individuals with object-oriented segmentation and ASD procedures help alleviate the unique demands placed on children with autism.
- The use of different automatons to enhance the lives of children on the autistic spectrum is an area that still lacks clear answers in this regard. It is a way to teach youngsters with autism how to replicate hand motions as they talk.
- Wearable devices are used in all categories of autism assessment methods, including electromyography (EMG), pulse oximetry, global positioning systems (GPS), and others. Any device, or even an entire garment, might include a sensor.
- DL is a big question in ASD diagnosis, and there are many potential applications for it, such as multi-sided databases and brain imaging.

Furthermore, there are a number of issues brought up by the ASD that incorporates devices with an Internet of Things foundation, such as the following:

- *Integrity*: All data must remain undamaged and safe while it travels from one device to another and finally reaches its destination.
- *Availability*: In the event that various threats need it, availability guarantees that the authorized part may access any and all Internet of Things (IoT)-based healthcare services, whether those services are located locally, in the cloud, or globally.
- *Self-healing*: Due to the potential for medical equipment failure, self-healing capabilities are crucial for networks based on the Internet of Things. It follows that supplementary interface devices should provide at least some degree of protection.

2.4. Real-Time Healthcare Evaluation Through Sensor Data Transformation

i. Introduction

The healthcare landscape is facing increasingly complex challenges, particularly with rising rates of chronic illnesses and escalating healthcare expenditures, accentuated by aging populations globally [1, 2]. Traditional health monitoring methods have proven to be cumbersome and inadequate in meeting the demands of an aging society [7]. There is a pressing need for innovative healthcare solutions that can enhance patient care, reduce unnecessary hospital visits, and optimize healthcare costs. In India, government health expenditure is projected to rise significantly by 2060, highlighting the urgency for transformative changes in healthcare delivery [8].

The Internet of Things (IoT) holds significant promise in revolutionizing remote healthcare monitoring systems by bridging the gap between physical and digital realms [9]. This technology facilitates seamless communication and data exchange among interconnected devices, fostering real-time monitoring and informed decision-making in healthcare. IoT applications have garnered considerable attention in the medical industry, offering numerous possibilities for improving healthcare delivery and patient outcomes.

To address the challenges in healthcare, this study proposes an IoT Tiered Architecture (IoTTA) designed to efficiently process sensor data for real-time healthcare evaluation. The IoTTA framework aims to encompass the entire system architecture, enabling the development of robust software solutions that integrate diverse clinical inputs seamlessly.

This study is motivated by several critical healthcare issues. Firstly, the global population is aging rapidly, with projections indicating a substantial increase in individuals aged 60 and above by 2050 [1, 2]. Secondly, chronic illnesses such as, Chronic Obstructive Pulmonary Disease (COPD), Chronic Heart Failure (CHF) and Diabetes are on the rise, placing a significant burden on healthcare systems worldwide [3]. Thirdly, healthcare costs are escalating, as evidenced by substantial spending increases in hospital and medical services [5].

Existing medical IoT applications often lack cohesive frameworks and are implemented in narrow contexts. This study aims to give a thorough rundown of IoT technologies, propose the IoTTA framework for integrating healthcare systems, and illustrate potential applications of IoTTA in healthcare settings [12].

ii. Applications in healthcare based on the Internet of Things (IoT)

IoT technology is widely used to enhance remote health monitoring systems, particularly for individuals requiring constant monitoring due to chronic illnesses, disabilities, or advanced age. These technologies enable continuous monitoring, early problem detection, and expedited treatment without compromising patient independence or their desire to live at home. Below is a summary of IoT applications in long-term care, elder care, and emergency situations.

- *Remote Monitoring for Chronic Illnesses*
  - Studies like those by Ghosh et al. [15] focus on at-home monitoring devices for long-term illnesses, reducing readmissions through early anomaly detection.
  - ECGaaS, a system integrating Cloud Platform as a Service (PaaS) and body sensor networks, monitors ECG data [16].
  - Various systems monitor vital signs, including heart rate, blood pressure, and respiratory rate [11, 17-19].
- *Tracking Seniors in Care*
  - Telecare technologies, such as SilverLink by Gokhale et al. [16], aid in aging in place by analyzing sensor data for behavior deviations [21, 22].
  - Systems like H2U by authors [23] use wearable devices and biosensors for real-time support and health monitoring of the elderly.

- IoT-aware healthcare monitoring systems, as in [24], promptly alert caregivers or physicians in emergencies, with adaptable alert criteria.
- Solutions for medication adherence include RFID readers, smart pill boxes, and prescription reminders [25-27].

- *Emergency Response*
  - IoT emergency apps, as discussed by Guillame-Bert et al. [28], can detect anomalies and alert medical personnel, enabling timely response.
  - Telemedicine diagnosis and emergency telecare provide location-based emergency information and medical guidance [29].
  - Fall prevention and detection systems, such as those utilizing wearable devices or depth sensors [31-33], play a critical role in eldercare.

iii. *IoT Tiered Architecture (IoTTA)*

The Internet of Things (IoT) integrates various technologies into systems like IoTTA, structured into five levels shows in fig. 9: sensing, transmitting, processing, storing, and mining. In brief:

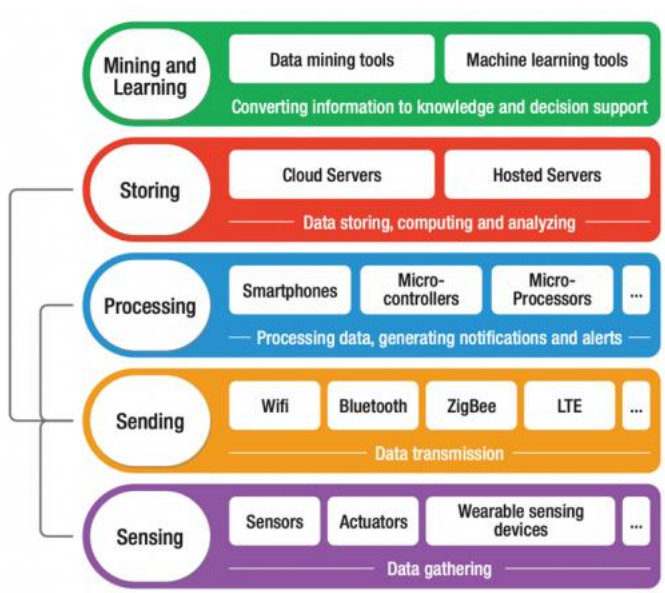


Figure. 9 Architecture of IoT multi-Tiered.

- *Sensing Layer:* Gathers health data from sensors monitoring vital signs and activity levels, crucial for healthcare applications.

- *Sending Layer:* Facilitates data transmission through technologies like Bluetooth, ZigBee, RFID, and Wi-Fi, ensuring efficient communication.
- *Processing Layer:* Involves data aggregation, analysis, and decision-making using hardware platforms and software applications.
- *Storing Layer:* Handles vast data storage, computation, and analysis, often utilizing cloud systems for effective management.
- *Learning and Mining:* Employs machine learning and data mining for insights and decision support, enhancing healthcare services.

IoTTA's potential extends to real-time clinical input and autonomous feedback, marking a shift in healthcare IoT applications toward advanced, self-learning systems.

iv. Transforming Sensor Data into Real-Time Healthcare Feedback: The Opportunities Of (IOTTA)

Recent research using IoT in healthcare may be broken down into three categories based on our analysis: monitoring, self-care, and clinical assistance. The advantages and disadvantages of each category of uses are shown in Table 3. This research uses the SHARP framework [37] to assess the benefits and drawbacks of the studies that were included in the review.

Table 3. Evaluation of studies using a delicately improved concept

Strengths	Studies that are relevant and Type of Application	Weaknesses
• Provides a means of identifying worsening health conditions before they become life-threatening. • Similar to [14], it offers individualized diagnoses. • Delivers very precise prediction models, similar to [19].	**Clinical Support** [7], [11-12], [15-16], [18], [20], [23-25], [30], [33-34],[36]	• Algorithms designed to aid clinicians are seldom used. • The data are not being mined efficiently, which limits the potential impact.
• Sustains remote, round-the-clock patient monitoring. • Enables online, real-time access to patients' medical records. • Offers precise detection using techniques similar to those described in [20], [22].	**Monitoring** [7], [10], [11-20], [22-25], [35- 36]	• Lack of follow-up after first monitoring. • With manual systems like the one described in [10], for instance, patients are responsible for taking their own readings and documenting the outcomes.

		• With the exception of [24], most systems don't allow for changes to be made during operation, such as the addition of additional sensors.
• Allows for a diagnosis to be made with a high degree of precision. • Offers high-quality home medication management, particularly in [26].	**Self-care** [23, 24], [27-30], [35]	• There is a lack of guidance and directions that have been proven effective in clinical settings. • Patient participation in medical decision-making remains low.

Real-time, Sustainable, Adaptive, Holistic, and Precise (or SHARP for short) is an acronym for five characteristics that are taken into account while designing healthcare systems. Table 3 shows that most implementations prioritise programmes that monitor patients or provide clinical assistance, whereas just a minority prioritise applications that encourage patients to take responsibility for their own treatment. Using IoTTA will allow for the creation of systems that value the gathering and analysis of data at different levels. Table II displays the penetration of each IoTTA layer by evaluated research. According to the paper's study, two subfields of healthcare IoT development self-care, machine learning and data mining account for the majority of the industry's expansion.

v. Care for Oneself

One of the most challenging jobs doctors have today is assisting patients in providing adequate self-care [50]. Nonadherence to medicines and food, and a delay in seeking medical treatment for worsening symptoms, are two of the most prominent causes of poor outcomes for heart failure patients who attempt to care for themselves [38]. The authors argued that empowering patients to care for themselves required more than just imparting medical knowledge; it also required teaching them how to keep track of their own symptoms and signs.

Table 4. Reviewed studies for applying IOTTA

Conducted a study in terms of references	Tier
[6-7], [10], [14-21], [23-25], [27-28], [30], [33], [35- 36]	Processing
[11], [19-20], [23-24], [30], [34-35]	Learning and Mining
[5-7], [10], [16-20], [23-25], [27-28], [30], [33], [35]	Sending

[5], [10-15], [16-21], [22-26], [28], [33-36]	Sensing
[6-7], [10], [14-21], [23-25], [27-28], [30], [33], [35- 36]	Storing

Patient-specific, real-time clinical feedback enabled by IoTTA in the future healthcare system may include instructions on how to take vitals, how to take medications, and advice for maintaining healthy ranges. These seem like efficient and inexpensive ways to help the elderly care for themselves at home. Also, customization of health solutions by adjusting to the persons characteristic plays an important role in increasing the quality of treatment [39].

vi. Machine Learning and Data Mining

Table 4, which indicates that there were fewer research efforts that really utilized the mining and learning phase in most clinical applications, which mainly work by comparing patient data to predetermined norms and then sounding an alarm if any discrepancy arises. Alerts in clinical support applications should generate from a last resort position in order to avoid inundation of emergency services in the event of a false alarm. In turn, questionnaires or interviews can be employed when the monitored variable has been identified as anomalous.

However, data mining technologies and machine learning tools could enhance IoT healthcare apps providing clinical support that helps patients more. Prediction and decision-support vocations are expected to decrease the need for clinical interventions. This means that feedback from patients will include suggestions on medication, good food, and exercise without professionals whatsoever.

2.5. Exploring the Integration of Cloud Analytics and Deep Learning in Patient Monitoring and Recommendation system.

In this comprehensive examination, the section navigates through the landscape of healthcare monitoring systems, encompassing both IoT and ML-based approaches, establishing their prevalence and smart functionalities [29-31]. A meticulous review and comparison of contemporary research materials are presented in Table 5, providing insights into the existing landscape.

Table 5. Monitoring patients with chronic diseases: a review of healthcare regimes.

Features	[1]	[3]	[8]	[16]	[20]	[21]
Issues that have been addressed	Chronic kidney disease (CKD)	Diabetes	Diabetes diagnosis	Temperature and pulse	Blood-pressure disorders	Chronic diseases
Architecture	Cloud-based hybrid (4-tier)	Zion China Architecture	3-tier	WSN and IEEE 802.11 are the foundations of this system.	A hybrid architecture that includes both local and cloud-based components (3-tier)	two-tier (Client and Cloud side)
Experiment domains	Cloud computing, Machine Learning	IoT, Machine Learning, and Cloud Computing	Big Data, IoT, Cloud, and Machine Learning are all terms used to describe the Internet of Things.	Internet of Things.	IoT, Machine learning, and cloud computing (three tiers)	Analytics, cloud computing and IoT.
Reliability	Low	High	High	Low	High	High
Tools for ensuring reliability and the environment in which they are employed	CloudSim package Windows Azure	Business intelligence, Azure ML, SQL	5.0 generations of wearable technology, 5G networks	Sensors and Raspberry Pi 3	Weka Spark package and MATLAB R2016b (9.1)	Amazon EC2
Functionality (Prediction/ Classification /Monitoring/ Analysis)	Classification	Prediction	Evaluation as well as Forecasting	Sense-making and Keeping an Eye On	Classification	Monitoring and Analysis
Exhibited items	Static	Dynamic	Environmentally responsible and economical	Stable	Context-aware	Static
Advice and suggestions	Negative	Negative	Affirmative	Negative	Negative	Negative
Cost	Modest	Modest	Modest	Modest	Raised	It's about right.
The difficulty of it all	Low	High	High	Medium	High	It's about right.
Parameters	Measures of Accuracy and F, as well as Error Rates	Normal glucose levels were detected.	Accuracy	The correctness of reading	Time, F-measurement Accuracy, and Precision	Accuracy of the ECG
Dataset size	Extremely tiny (306)	Large	Small	Small	MATLAB was used to produce a large dataset.	Huge

Efficiency results (Accuracy)	up to 97%	up to 87%	up to 92%	up to 95%	76–99%	up to 91%

There are several benefits of using an Internet of Things-enabled remote health monitoring system instead of conventional methods. Conversion of analog information into digital format is one of the factors for continuous monitoring of the patient. This promotes self-care on the part of patients and allows for early detection of chronic illnesses. A few postulations on relevant research articles are given below.

Shashikumar et al. [38] give an account of their efforts to conceptualize WIoT from technical, organizational, and logical standpoint in relation to wearable devices. Generally, an IoT architecture for wearables has got three major components: 1) The sensors get worn typically on several body parts; 2) The information acquired by the sensor may be transferred through Gateways connected to the Internet to the server or the cloud for storage and analysis; 3) This allows machine learning. Darshan et al. have investigated the role of IoT in healthcare and made a literature review on the same. In their proposed system, a multiple-layer: a) raw data should be put in through various sensors on the medical IoT devices (ECG sensor, EEG sensor, skin-temperature sensor, etc.).

Here, we take the information that has been filtered, processed, and categorized in order to analyze and predict. Tarassenko et al. [39] offered an introduction to the Internet of Things, its past and future, and how this relates to healthcare. Essentially, the concept of the Internet of Things evolved from Electronic Data Interchange (EDI) in 1999 to the Internet of People (Internet-M-Internet) and is now a distinct entity. Furthermore, the Internet of Things benefits could also cover many different industries by other means, including implantable medical devices connecting with websites, medical professionals, and patients while being part of healthcare delivery.

When it comes to e-health and the Internet of Things, Van et al. [40] provide a paradigm for intelligently providing medical services. The following are the stages of the proposed Internet of Things-based paradigm: The four main components of telemedicine are: A) Patient Records, which contain all data regarding the patient, acquired in real-time or from a dataset; B) Clinical Decision System, which provides DSS for the physicians based on connected knowledge; C) Remotely monitoring the patient through the use of sensors attached to the human body to collect data; and

D) Remote treatment, a crucial step because it facilitates contact with healthcare centers by easily, that gives the rural population better healthcare.

Yoon et al. [41] provide the idea of how the Internet of Things (IoT) contributes to and enhances healthcare facilities. There are three tiers to the suggested system, the first of which is for sensing, which is the process of gathering data or information in real-time using sensors (temperature sensor, pulse rate sensor, etc.). The second level of transmission involves sensors sending their collected information to a data server. The doctor may view patient information and make diagnoses from inside the server with Tier-3 access. The suggested work consists of both digital (an Android app and a web page) and physical (an ATMEL 89s52 microcontroller, temperature sensor, pulse rate sensor, serial port, A/D converter, and IC-7805 voltage regulator) components.

Barfod [42] offers a comprehensive review of IoT's potential in healthcare. He talks about innovative approaches of providing healthcare, such as mHealth and 6LoWPAN-based healthcare. The mHealth framework consists of three main parts: 1) The Layer for Collecting Data There is a layer 2 for storing data and a layer 3 for processing it. The first step of a 6LoWPAN-based healthcare system is for sensors to collect data, and then the gateway would convert the data to IPV6 and send it to the server. They go on their talk about the latest complete architecture for healthcare smart systems. Individuals with chronic diseases like stroke, diabetes, cancer, etc., may efficiently monitor their own health with the help of a healthcare monitoring system developed by Hillman et al. [43], which makes use of the Internet of Things (IoT) and classifier algorithms for prediction. The suggested method for monitoring stroke patients consists of three parts: 1) The hardware tier consists of the microcontroller, blood pressure monitor, and glucose analyzer. Finally, at the application layer (web environment, cloud server), machine learning (ML) techniques such as Naive Bayes and Random Forest are deployed. The predictive accuracy of the Random Forest algorithm is 93%.

In [44], McGaughey et al. propose an IoT-based cancer care system hosted in the cloud. The method used in this research involves attaching a body wireless sensor network (BWSN) to a patient and then collecting and converting data through the Zigbee protocol before saving it to a data set or the cloud for analysis. Conceptually, the Internet of Things (IoT) and its multi-tiered architecture 1) The patient is outfitted with a network of sensors that are permanently attached to his or her body. 2) A management processing layer that acts as a conduit for information remapping. Fourth, the applications layer is where the action is on the Internet of Things since that's where all the cool stuff occurs, including information processing, analytics, security, and device administration. The challenges associated with implementing IoT in healthcare systems were analyzed by Gao et al. [45] and discussed further. IoT-based healthcare monitoring system architecture proposed by Cecchinel et al. [46] uses ML algorithms to identify early warning symptoms of heart illness. The suggested system consists of three levels: At the first level, data is acquired via Internet of Things sensors carried by the user. Level 2 uses Apache HBase to store petabytes of information. Level-3's data analytics skills are particularly useful in the field of cardiovascular disease forecasting. Machine learning algorithms (MLA) are implemented here. The results produced by the system are clearly superior.

As suggested by Chen et al. [47], ensuring security via the use of IoT and cloud computing. Fuzzy Rule is an innovative approach to diagnosing various diseases that they present. There are a total of eight parts that make up the suggested system. These parts include medical sensors, the UCI Repository Dataset, cloud computing, data aggregation, a fuzzy temporal neural classifier, and more. The code was written in JAVA, and Amazon's cloud servers hosted the finished application. K-NN, DT, NB, and SVM are four of the most common classifiers used in medical diagnosis. The final results are as follows: K- NN achieves 92% accuracy, DT achieves 95% accuracy, NB achieves 85% accuracy, and SVM achieves 80% accuracy.

An intelligent method is presented by Chok et al. [48] for student diagnostics. The first step in the proposed three-stage process consists of data gathering from the IoT devices. The collected data are then passed onto an intermediary cloud server through the gateway. Second, the diagnosis should be performed after data processing and upon the features extraction and healthcare attributes measurement, analysis, etc. Finally, a health alert is sent to the family of the patient. The classifiers used are DT, k-NN, NB, and SVM.

While many studies stress that ML improves early detection, personalized care and reduces clinic workloads, we have to notice certain practice issues in order for the system to work well and not face problems in the future. Problems in real projects do not always coincide with what is found in ideal theoretical studies. Issues can be related to hospitals using aged IT systems, not all patients using wearable devices properly and maintaining devices, setting up their data and dealing with network problems during operations in poor-resource places. Frustrating false alarms, occasional system issues and unreliable sensor readings continue to affect how clinicians accept and trust wearable devices.

Ensuring the privacy and safety of data gets more important as we rely on wearable sensors and remote monitoring systems more. The ongoing flow of health information leads people to ask how such data is protected, who can gain access to it and how companies stay compliant with privacy regulations. Should these problems be left unrepaired, hesitation by both institutions and patients may prevent broad acceptance.

As a result, many interesting approaches, including systems that process information locally and, in the cloud, AI-enabled triage bots and systems that get relevant alerts fast, are now being evaluated in industry tests, experiments and small-scale healthcare projects. Although they give a good idea of what's coming, they tend not to be acknowledged by academic reviews. Consequently, the process of reviewing technology should now include greater use of recent and varied evidence such as current practices and the feedback of health experts in different environments.

Researchers can use experiences from multiple types of healthcare settings to help ML- and IoT-based health care systems perform well in real life. This will improve the design of systems and guarantee that their uses benefit patients, can handle many situations and influence real-world healthcare.

2.6.Research Gaps

This opens a very significant field of study in the health care world. Numerous studies are being carried out to understand IoT, ML, and AI in health care. However, compared to standard IoT-based health care applications system, ML-based medical health care applications present a significant extra barrier. The app has one main function: to visualize the data obtained from the various sensors. It is extremely difficult to maintain, monitor, and power all the devices simultaneously, since the sensors are embedded in them. Following this, the research gaps were identified.

- Remote Critical State Monitoring: Several health care applications based on machine learning today do not have reliable systems for the remote identification of a patient in urgent condition based on vital signs and medical rules in active contexts. Existing research [1-4], [8-10], [11-14], [17-18], [35-36] suggests potential in Theory; however, there exist hurdles for practical implementation.
- Real-Time Health Assessment for Patients with Chronic & lifestyle disorders Diseases, like ASD, blood pressure and heart attack: Even considering recent advancements in healthcare monitoring with AAL devices, the real-time assessment of health status using Machine Learning models for patients with chronic diseases and ASD is still missing [15-19], [21-25], [37-40], [44-51]. This gap imposes a limitation on the customizing timely interventions.
- Enhanced Big Data Analysis: These challenges involve three specific cases that illustrate how unstructured and imbalanced datasets could be handled for largescale analysis [20-22], [28-30], [38], [52-55], [60-62]. Enhanced ML techniques provide deeper insights into complex health data.
- Real-Time ML-Based Vital Sign Monitoring System: A real-time machine-learning-based intelligent information modeling system that enables all forms of vital sign monitoring, both local and cloud-based, is yet to be invented [23-27], [31-34], [66-69]. The introduction of such a system would bring about a radical change to patient care supported with instant accurate health assessments overall.

2.7. Chapter Summary

In this chapter of Literature Review, the work presents a survey of integrating machine learning and IoT in healthcare, focused on live monitoring of patients' vital signs. The influence distinguishing machine learning and patient care, early warning systems as support for clinical decisions, AI-based approaches for the assessment of ASD, and the proposal of an Internet of Things Tiered Architecture (IoTTA) for healthcare evaluation are discussed. The research gaps left include remote monitoring, real-time assessments over time for chronic diseases, big data analytics, and ML-based vital sign monitoring systems as important so that personalized interventions could be possible for better patient status.

Chapter 3: Proposing a Novel Real-Time Vital Sign Monitoring System Using Machine Learning

Overview

This chapter addresses the Smart Patient Monitoring and Recommendation (SPMR) framework as unified by means of DL, cloud analytics, and IoT principles to monitor the vital signs of patients in real time. The components of SPMR are discussed, including DL algorithms and cloud-based analytics, and IoT principles of data collection and transmission. It further details data collection and preparation processes required in the training of machine learning models within the SPMR framework. Besides, it elaborates on the model evaluation methodologies in terms of performance metrics, performing comparative analysis with similar models and testing the efficiency and safety of SPMR when implemented in health monitoring systems.

3.1.Introduction

To finalize our model for "Smart Patient Monitoring and Recommendation (SPMR) using Cloud Analytics and Deep Learning," we passed through a series of scrupulous tests on our alternating modes and schemes. Our testing phases comprised overall evaluations along the lines of reliability, functionality, cost, and efficacy. We mined insights from a comparative analysis that basically drew a detailed examination of the healthcare regimes that had been presented in the literature review section.

The testing features included parameters like the relative accuracy, precision, F-measurement, and values for error rates. We took time to study all exhibiting features, architecture, experiment domains, reliability, tools employed, functionality, provides advice and suggestions, cost, difficult to implement, parameters, data set size, and efficiency results from the reviewed healthcare regimes. By systematically analyzing these aspects, we tried to ensure that our decided model would reliably pull off a standard function as per the outlined requirements of patient monitoring of chronic diseases. Such an elaborate testing approach would provide us with good ground for making an informed decision in the selection of the most appropriate model for our research, enhancing the robustness and effectiveness of the proposed SPMR framework.

3.2. SPMR Proposed Architecture

AI-enabled, IoT, deep learning, and cloud computing gadgets have all found a home in modern healthcare facilities. Patients with chronic conditions can benefit from these hybrid technologies, which provide improved patient monitoring and referral systems. The SPMR framework allows hospitals and caregivers to provide better home care for patients. A DL model applied to vital signs and context data helps to acquire, store, monitor, and forecast the patient's health state. In Fig. 10, you can see the proposed SPMR's four-layer architectural structure. Sects. 3.2.1–3.2.4 describe the various layers.

3.2.1. Ambient Assisted Living Layer 1 (AAL)

Define Patients' vital signs and environmental conditions can be monitored and recorded using the AAL system and open-source e-health software such as My Signals [27]. (Humidity and Temperature). Additionally, AAL systems always keep track of the patient’s whereabouts and activity. Each AAL system has a distinct identifier within the cloud architecture. The patient's condition determines which devices are chosen. E-health systems support an extensive array of connectivity options and specialized medical sensors. A support system for sensors that detect light, smoke, temperature, and humidity is provided by the AAL layer. A layer that monitors key signs while simultaneously recording the surroundings around it.

3.2.2. Local Intelligent Processing at The Second Layer (LIP)

The LIP module collects, aggregates, stores, and processes data that is sent over intermediate communication protocols and makes it available to the rest of the system. Because of this, it may be used both in offline and online environments. It differs from previous frameworks in that it offers high-performance offline learning and recommendations. It includes the following parts:

i. Edge Device

IoT Gateway is another name for this device. Low-level data from sensors, intelligent devices, and the cloud can be exchanged and processed locally using hardware or software.

ii. An On-Site Local Processing and Storage Facility Unit (LPSU)

An appropriate format is used to store and transform the AAL layer's data for the DL model in LPSU. This unit is also responsible for transforming features. Data exploration is carried out using a variety of strategies, including normalization. LPM receives the reworked components. Also, the LPSU has a Cloud Monitoring Module (CMM) that updates the general medical rules and medical records on a regular basis (CMM).

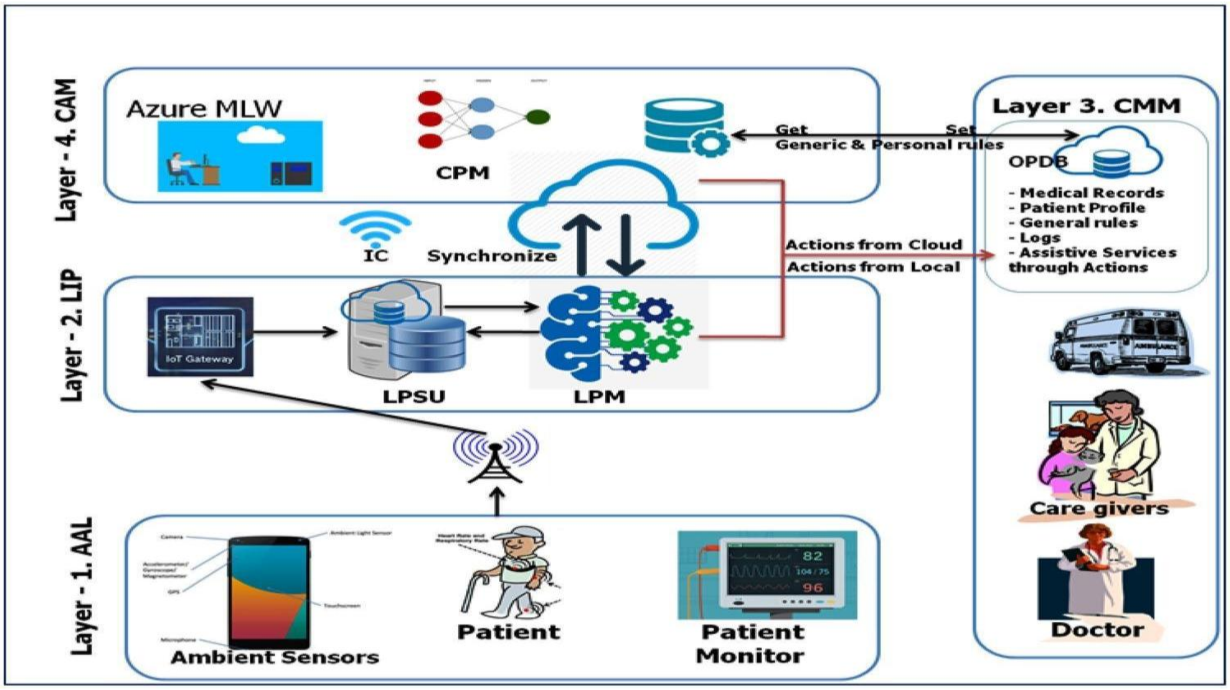


Figure 10. Framework components and the proposed architecture of Smart Patient Monitoring and Recommendation (SPMR).

iii. The Suggested Local Predictive Model Has the Following Characteristics: (LPM)

Patients' health status and emergency scenarios are classified by LPM on the local side. The model in [28] downloads the model from the cloud, in contrast to this unit. Vital signs and current AAL data are used to develop the LPM unit's own categorization and prediction model. In the event of a network outage, a lack of cloud services, or any other type of emergency, the model will hold. Once the patient's health state has been accurately assessed, this layer takes the required and appropriate steps to contact medical professionals, caretakers, or other support services. The diagram in Fig. 11 provides an overview of the LIP model development and prediction process utilizing DL based on new CCE optimization. Sect. 3.2.5 provides a thorough explanation of the algorithm in use.

3.2.3. Cloud Monitoring Module Is Located in Layer 3. (CMM)

The term "knowledge module" refers to the CMM as a unit of information. Clouds with patient-specific information, assistance services, and knowledge databases are part of the package. Two or more clouds can be included in the CMM if the right permissions are obtained. When allowed and linked to these clouds, SPMR monitors the CMM. Medical specialists, hospitals, and carers are all involved in providing assistance. The most important aspects are covered here.

i. Online Patent Database (OPDB)

Information on the patient, such as age, sex, and weight, can be found in the OPDB. This program is also responsible for keeping track of a patient's medical records and investigation results, as well as their treatment and assistance plans, food, and any specific thresholds for vital signs. An OPDB cloud storage account is provided and monitored by a smart healthcare center or hospital. When it comes to patient-specific regulations and updates, OPDB and the medical cloud are in sync [29-30].

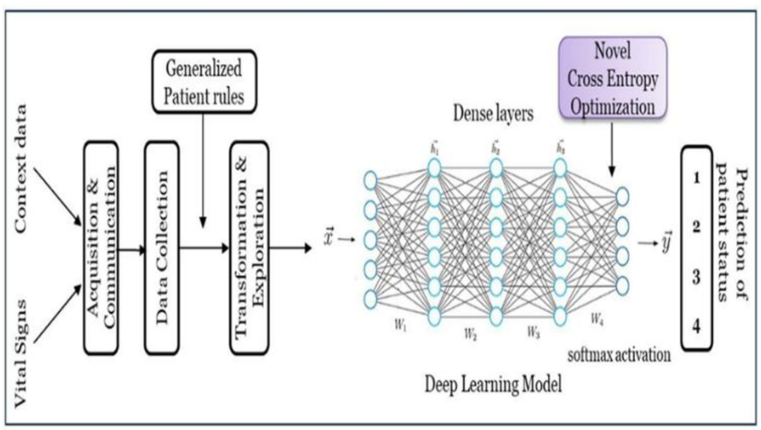


Figure 11. Proposed LPM (Lifestyle Prediction Mechanism) prediction mechanism.

ii. (MC) The Medical Cloud

Symptoms, vital signs to monitor, and broad rule ranges are all included in this cloud of current medical knowledge. Medical knowledge is based on the most recent studies and generic norms in MC, which are updated regularly. The OPDB syncs up with this information.

iii. Assistive Services

Services supplied by a smart healthcare facility or hospital are also included in this category. Also included in this is the patient's family, friends, and caretakers. When a patient's health began to decline or an emergency occurred, these services were activated. The LIP and CAM layers send alerts to the team, which responds remotely to any issues that arise.

3.2.4. Cloud Four Layers of Monitoring and Cloud Analytics Proposed (CAM)

Physically situated cloud components that adhere to strict privacy standards and legislation can be found in this tier. The massive amounts of data generated by AAL are housed on massive cloud infrastructure. It's also accessible as a subscription service on several platforms (Software as a Service). To meet the needs of large data analysis, this framework was developed on an expandable cloud platform and is fast, efficient, and accurate [31, 32]. Together with layers 2 and 3, this layer accumulates the preceding two levels' data and rules. The CAM-administered machine learning model can analyse massive amounts of data and trends in order to anticipate a patient's health status. The GCP (Google Cloud Platform) Cloud Predictive Model (CPM) is included in this module and may be accessed online. The model's inputs and outputs are synchronized by layer 2, which is the second layer. The following components are included in this module:

i. Workspace For GCP Machine Learning (MLW)

To speed up prediction and classification, GCP-MLW [33] stores and distributes computation over many computer clusters. Machine learning models may be built and deployed using this programmed. ML Gallery, ML Studio, and Management of ML Web Services are all included in Microsoft's ML Workspace.

ii. To Handle Large Data Sets, The Predictive Model (CPM) Is Implemented Using GCP Machine Learning (ML).

There are typically five key steps to knowledge discovery using CPM: preprocessing, model training, testing and evaluating, and finally deployment. Microsoft's GCP ML platform covers all aspects of machine learning. The ML model was built and deployed using GCP's ML service. Packages and APIs for building machine learning models are available through the GCP ML service, which may be used to construct web and mobile apps using these models. Fig. 12 depicts the use of the GCP ML service for the development and deployment of a predictive model.

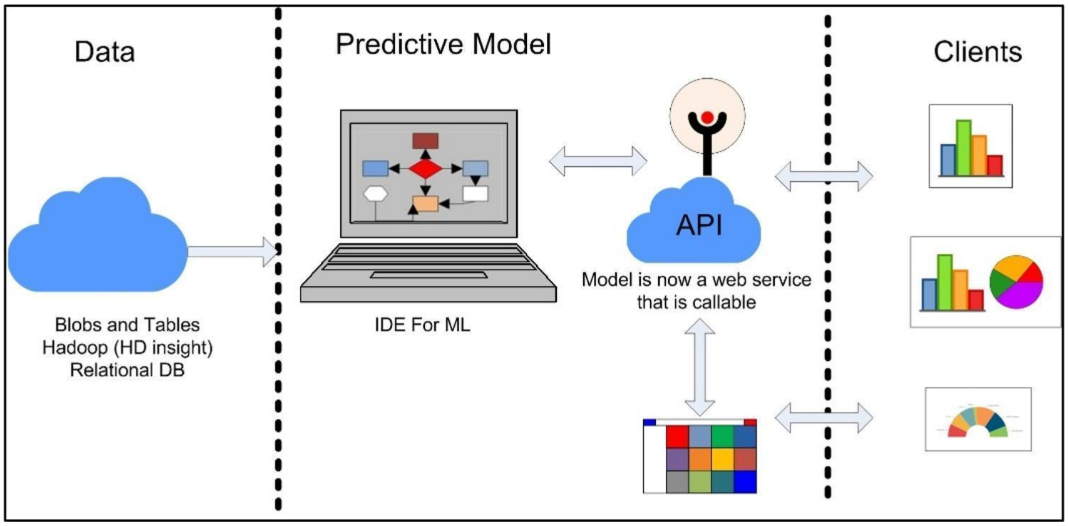


Figure 12. Predictive models built and deployed using the Google Cloud Platform ML service.

3.2.5. SPMR'S Suggested DL Technique for LPM and CPM

In the higher layer, AAL sends all of the recorded data. For the purposes of LPM and CPM, data are gathered, aggregated, stored, and analyzed in LIP. Predictive models are designed to demonstrate the most accurate categorical categorization accuracy for the benefit of patients and healthcare providers. The data has been processed using the technique shown below. The stages of the model development process are outlined in the following paragraphs.

i. Data Gathering and Aggregation

Unstructured data gathered from sensors and offline devices, alongside data obtained via the MySignals platform, is captured and buffered by the Edge device, according to SPMR. On the edge, raw data may be translated from a low-degree to a higher-degree abstraction using the High-Level Feature Provider (HLPF), also known as the Context Aggregator [35].

Notations	Algorithm 1: DL algorithm for LPM amd CPM
Dataset with traits **1** through **n**:	**Framework Inputs:** AAL data and Vital Signs

$A \ = \ a_1, a_2, \ldots\ldots\ldots\ldots a_n$ $W^1 \ = w^1, w^1, \ldots\ldots\ldots\ldots w^1$ W^h**:** denotes the weight that layer ***h*** set. W^1 **:** shows the weight that was set at the first buried layer. *Step functions are represented by **f ()**.* Activation function activation *functions are represented by **f (Z).*** $h_j^i \ = \ f(Z)$ The activation function used in hidden layers is rectified liner unit "relu". ● Output of linear equation = **Z** ● bias = **b** ● attribute value = **a** ● overall amount of features = **n** ● number of features extracted = **m** ● average of the training sets = α ● Training sample standard deviation = σ represents i^{th} neuron in i^{th} hidden layer. Superscript *i* denotes layer, subscripts neuron number. Number of classes = **k** $\hat{y}$ is probability set for { y_1, y_2, y_3, y_4} class labels i.e, Normal, Alert, Warning, and Emergency.	**Model Phases:** **Input:** $A \ = \ a_1, a_2, \ldots\ldots\ldots\ldots a_n$ **I. Pre-process:** 1. Convert types to numeric 2. Apply **z - Score** for normalization: $z - \ score \ = \dfrac{a \ - \ \alpha}{\sigma}$ **II. Feature Engineering:** Extract features as per contexts $A \ = a_1, a_2, \ldots\ldots\ldots\ldots a_m$ **III. Model Building (Learn Phase):** 1. Calculate $Z \ = \sum_{i=1}^{m} \ W_i^h A_i \ + \ b$ 2. Feed **Z** into ***f(Z),*** so that we get output at each hidden layer. $h_i^i \ = \ f(Z)$ 3. Calculate the probability score of class C_j given sample a_i. $P \ (C_j \mid a_i) \ = \dfrac{exp(Z_j)}{\sum_{k=1}^{4} \ exp \ (Z_k)}$ **IV. Test / Prediction:** $\hat{y} \ = \ argmax \ \ _{j\epsilon \{1,2,3,4\}} P \ (C_j \mid a_i)$ Apply softmax function at output layer

softmax (Z) squashes the vector **[Z]** of real values into real values in the range [0,1] that add up to 1. Where μ_i is proposed individual Cross Entropy (CE)	$$softmax\ (Z) = \frac{e^{Zi}}{\sum_i e^{Zi}}$$ **V. Optimization:** Apply proposed CCE Optimization and calculate **E(W)**: $$E(W) = -\sum_{i=1}^{k} \mu_i$$ **Output:** $$\hat{y} = \{Warning, Normal, Alert, Emergency\}$$

Once the MySignals kit and HLFP data is converted into a unified contextual state by the LPSU, it is stored in a data repository. Data in the 'csv' format relating to the patient's physiological signals, environmental circumstances, and activities are included inside this section for the duration of the time period indicated. Numbers are used to represent both numerical and categorical data in DL models. As a result, the data are transformed into a numerical representation that is compatible with the DL model used in LIP and CAM.

Additionally, the z-score normalization technique was employed in this study to standardize (normalize) the data. Each neuron in a Deep Neural Network (DNN) conducts arithmetic operations on the inputs and weights it receives.

ii. Transformation of Data

After the pre-procedure assessments are complete, the numerical value of an attribute is represented as a straightforward vector. If you've ever trained and operated a deep learning model using tensor transformation, then you'll know exactly what we're talking about here. Using this transformation, the model's features can be translated into the format that the model employs to make computations go more quickly and with less effort. Tensors represent vectors and matrices in greater dimensions. Within its internal structure, TensorFlow encapsulates tensors by utilizing collections of elemental data types that are n-dimensional in dimension. Tensors have the capability of extracting the maximum amount of performance from the System's hardware.

Primitives for optimal DL are also supplied for things like Activations, Pooling, and Inner Products, among other things.

iii. Feature Engineering and Design

The Spearman's correlation coefficient is deemed more suited for healthcare data that includes outliers (emergency cases in our study) [36]. For this purpose, we used the metric Spearman's correlation coefficient to identify the most correlated of n characteristics from the n input features. The DL model has been given the tensors of the m correlated features. A multitude of disease-specific parameters, such as symptoms, vital signs, and so on, have been retrieved using the Spearman correlation coefficient for a variety of chronic illnesses. HR, DBP, SBP, RR, and symptoms were substantially linked with class designations in our research of BP patients.

We employed tenfold stratified cross-validation to deal with the unbalanced dataset based on the reference [37]. The F-score of the feature selection approach was 0.98. For consistency in the training and testing sets, k-fold stratified cross-validation assures an equal percentage of each class.

iv. Construction of a Model

In our pursuit of selecting the optimal model for "Smart Patient Monitoring and Recommendation (SPMR) using Cloud Analytics and Deep Learning," we conducted a thorough analysis, comparing key features and attributes across various healthcare regimes. Table 6. summarizes the review of different healthcare regimes, highlighting essential aspects such as issues addressed, architecture, experiment domains, reliability, tools, functionality, exhibited items, advice, cost, difficulty, parameters, dataset size, and efficiency results.

Table 6. A Sample Dataset of Patients with High Blood Pressure

Time Stamp	DBP	SpO2	SBP	DBP	RR	HR	Act	Amb	L_Act	Symp	Med	Class
02-02-2019 00:00	74	98	111	74	12	66	5	0	5	0	0	1
02-02-2019 04:30	107	64	52	107	23	180	3	2	4	56	1	4

06-01-2019 03:30	118	92	159	118	13	105	3	0	3	6	0	3
06-01-2019 22:45	89	93	130	87	6	97	1	1	6	26	1	2

This comparative analysis helped us in selecting an optimal model based on rigorous testing and specific criteria, ensuring that our chosen model aligns with the desired attributes for effective patient monitoring in the proposed SPMR framework.

In NN, the output is determined by the input X and the weighted sum of the inputs:

$$Z = WTX + b \qquad (1)$$

Z stands for a linear equation, WT stands for weights, and b stands for bias. The step function predicts either a binary or multi-class output based on the value of Z. Discrete output is the term for this type of output.

Layers of computing are used to discover patterns from input data using the DL approach. Some information is taken at each layer, and the output of one layer is sent to the next [38]. In the realm of machine learning, it is recognized as a Deep Neural Network (DNN) and holds significance as a strong ML technique [39]. In order to predict a recurrent neural network (RNNs), convolutional neural networks (CNNs), and multilayer perceptron's (MLPs) are three popular designs that have been developed as part of Deep Learning. Their purpose is to determine the health state or sickness of a patient by studying the vital signs of the patient and the environmental stimuli that they are exposed to. Up to and including three tiers, SPMR's five-layer deep model learning procedure made use of an optimal parameter configuration (MLP). Phases of CPM for each kind of patient are presented in Fig. 13 individually. The anticipated CCE optimization is described in Section 3.2.6.

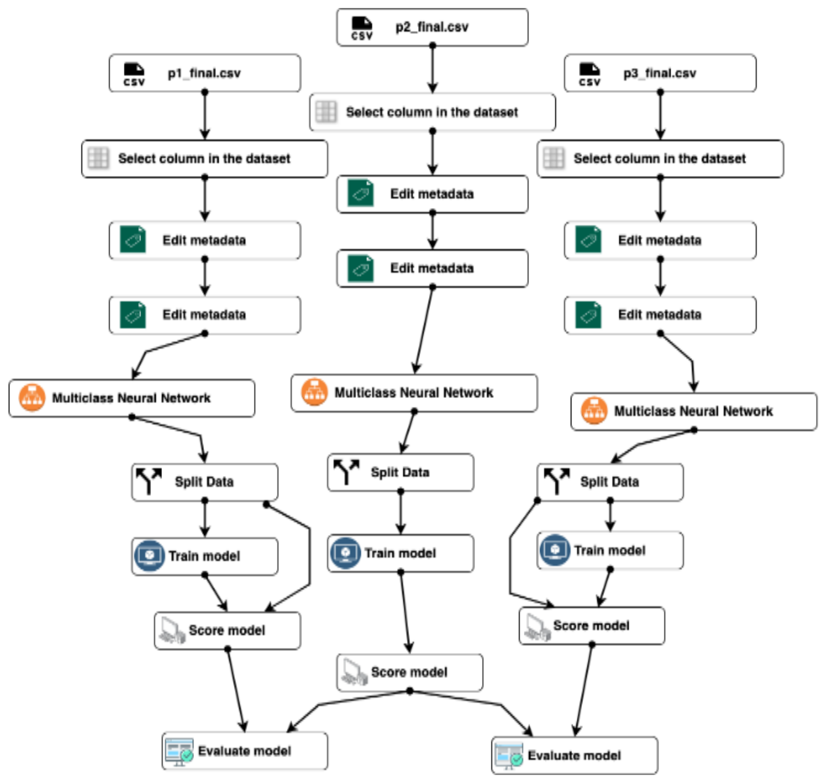


Figure 13. Phases of (CPM) Cloud Predictive Models (DL) implementation on the GCP cloud.

vi. Evaluation of the Model

The models were built rigorously according to the procedures spelled out above, based on deep learning optimization, coupled with a method called Categorical Cross Entropy. A real computing platform-Google Cloud Platform-was used to measure the efficacy of the models, with evaluation techniques including correlation-based feature selection and stratified sampling.

By deploying a novel CCE optimization technique and the power of cloud computing-Google Cloud Platform-the models have had an extraordinary ability to perform deep analysis with much data, particularly unstructured and imbalanced data. This approach achieves robustness and adaptability to real-world scenarios in healthcare.

The balance of the dataset was not carried out via SMOTE or GAN, which is crucial in maintaining the genuineness of the data and its representativeness of actual scenarios since the inherent characteristics of the dataset and specific study objectives guided the choice.

Driven by patient data and contextual information, the classifier proves effective in predicting the patient's health status. The classifier incorporates false alarm minimization strategies to achieve balanced sensitivity and specificity, maximizing the accuracy of classification. This novel classifier not only provides reliable predictions but also reduces unnecessary alerts, thereby enhancing the efficiency of the healthcare monitoring system.

In similar semesters, making requests for assistance revolves around a core set of processes. This embraces the seamless amalgamation of patient data, the invocation of the predictive model, and the interpretation of the outputs so produced. Really precise work on the entire set guarantees that the system operates accurately and credibly, providing a foundation for a highly efficient healthcare support system.

vii. Security Measures and Threat Evaluation

The robustness of the security measures proposed in "Smart Patient Monitoring and Recommendation (SPMR) using Cloud Analytics and Deep Learning" is paramount. This section gives a comprehensive overview of the security measures of the SPMR framework: an emphasis on their effectiveness against potential threats

- Encryption Protocols and Data Integrity: SPMR utilizes state-of-the-art encryption protocols to protect patient data during transmission and storage. Strong encryption algorithms guarantee data confidentiality and integrity to avoid unauthorized access and tampering.
- Access Control: The access control mechanisms enable the regulation of user access to sensitive healthcare information. Role-based access means that specific patient data can only be accessed by people who are authorized, such as medical professionals and caregivers, boosting overall system security.

- Constant Monitoring: The SPMR approach to security emphasizes constant monitoring. The system has introduced anomaly detection mechanisms to detect and address abnormal patterns or activities that will signal the administrator in real-time about possible security threats.
- Offline Security: With no connection to the Internet or the cloud, SPMR keeps itself secure using its built-in offline security provisions. It therefore continues to deliver on-the-spot preventive measures and treatments, even in emergency situations.
- Threat evaluation, countermeasures: Threat evaluation would comprehensively ascertain the possible threats posed to the healthcare monitoring system. Based on such evaluation, countermeasures, preventive and responsive, are instituted as safeguards against extensive security threats.

3.2.6. Proposed CCE (Categorical Cross Entropy) Optimization Algorithm

For the suggested DL, a unique CCE cost optimization is used. Our key aim is to minimize CCE losses in our model while using the entire training dataset. To build a fresh list of novel CCEs, the following algorithm is employed. As a result of the updated Cross Entropy (CE) values, Deep learning makes use of a number of different optimization strategies, some of which include stochastic gradient descent (SGD) and adaptive gradient descent (AdaGrad). could potentially lead to faster convergence. Average CE loss is calculated by removing the chance of an event that is much more likely than the average CE loss. When fewer epochs are used, the DL algorithms achieve their goal quicker [40-44].

Algorithm 2: Optimizations for the CCE
Inputs: Actual probability list *(P)* Predicted probability list *(Q)* Initialize the List of resulting cross entropy *R* and variables *i, j* and *Mean_CE* *for i to length (P):*   *Calculate (CE) as [-sum ([P[i]*log (Q[i])]*   *Append CE for each input to lisr R* *mean_CE = sum (R)/length (P)* *for j to length (R):*

if (R[j] > mean_CE):
R[j] = (R[j] - mean_CE)

Outputs: New *CE* obtained in list *R*

Where log(), sum(), and length() are implicit function for corresponding function-alities

i. A Mathematical Model is Discussed in Detail

After calculating the individual CE errors, first determine the mean CCE.

$$E(W) =-1/N \sum(i-1)\ \hat{}k\ y\_i \log (\grave{y}\acute{}) \qquad (2)$$

Based on μ_i, where μ_i is the new individual CE, compute Fresh CCE, E(W)

$$\mu\_i\ (3) = y\_i \log (\grave{y}\acute{}) - E(W) \text{ if } y\_i \log (\grave{y}\acute{}) > E(W) \qquad (3)$$

The more recent CE vector μ_i serves as the foundation for the new CCE and may be written as:

$$E(W) =-\sum (i-1)\hat{}k\ \mu\_i$$

3.3. Setup Experiment

To test the credibility of SPMR and its constituent DL models, an experimental case study is offered here. Patients with persistent Blood Pressure (BP) issues can benefit from this study, which is currently being monitored. Patients with hypertension (P1), hypotension (P2), and normal blood pressure (P3) are all under observation [44-45].

3.3.1. Data Simulation for Long-Term Patient Monitoring.

Due to a lack of detailed long-term data for patients with chronic problems such as hypertension, a simulated database was put together and is shown in Table 7. This database records important patient data gathered each 15 minutes for a period of one year from information in the MIMIC-II database from PhysioNet, for three different individuals. Similar data was added to the main dataset by using e-Medical IoT devices (My Signals) and joined to make a comprehensive group for testing.

We used parameters that are clinically used and got advice from healthcare experts to keep the data realistic. Using this process, the reliability and relevance of the data are both improved.

The system was built according to SPMR principles to help with context-aware monitor transactions. It records the patient's activity movements, start and end times, along with heart rate, breathing rate, blood oxygen saturation, blood pressure, symptoms, drugs taken and surrounding conditions. In CMM, doctors and caregivers monitor and operate the sensors included in Ambient Assisted Living (AAL) ecosystems [46]

Patient data is grouped as normal, alert, warning or emergency depending on the given condition, as noted in Table 7. However, as the dataset is not evenly balanced, most normal cases are classified as normal instead of critical, as standard approaches tend to do. This often causes wrong reports and confused treatment. With SPMR, groups of patients can be put together based on their symptoms, bodily signs, medications and homes which permits more precise care and tracking.

Table 7. Description of the Data Set Background for Three Patients in the SPMR

Normal	Class	Emergency	Alert	Warning	Total contexts
9307	(P1) Hypertensive	175	2404	23347	9307
19455	(P2) Hypotensive	148	1627	14003	19455
12517	Normotensive (P3)	109	1186	21421	35233

A year of vital signs, ambient circumstances, symptoms, activities, and medicine (Med) are collected by SPMR as a big data source, encompassing metrics such as respiration rate (RR), heart rate, peripheral oxygen saturation (SPO), diastolic blood pressure (DBP), and systolic blood pressure (SBP) are the vital indicators observed in this case study (SpO2). For long-term monitoring of biomedical data, synthetic data creation has demonstrated its dependability in earlier research [47]. Class descriptions for unbalanced datasets may be found in Table 8 (see below). General medical criteria can only categories the data into normal and abnormal categories since the dataset is so unbalanced. False positives result from this categorization, putting patients at danger of receiving the wrong medicine and care. With the use of SPMR, it is now possible to divide patients into several groups based on their activities, vital signs, symptoms, surrounding circumstances, and current drug intake.

Table 8. Classification based on the medical model and actions administered to the patient.

According to personal medical guidelines, the circumstantial categorization in Table 9 is utilised

Action	Classification	Class
Call/SMS your doctor or physician to schedule an appointment and review your medical history.	A condition of alert or if more than two vital parameters are within the warning range; and (symptoms greater than zero, or medication is equal to 1)	Alert
There is no action.	All vital signs are within normal limits. In other words, there are Zero - (0) symptoms.	Normal
Send an alert to caretakers via Monitor or use SMS via phone	Any vital signs that are in the danger zone; or medication that is 1, or symptoms that are greater than 0	Warning
Call an ambulance, oxygen, a doctor, or anyone else who can help in an emergency.	More than two alert range vital signs and (symptoms greater than 0, or medication is equal to 1)	Emergency

to anticipate classes. In addition, it lists the activities that must be completed in order to meet the expected class's requirements.

Table 9. Description of the dataset's attributes, as well as their type and range.

Attribute Name and Symbol	Format/Type	Unit/Range
Vital Signs (SBP, HR, DBP, SPO2 and RR)	All Numeric	(50–230 mm/Hg, 30–220 beats/min, 30–140 mm/Hg, 40–100 (%), 05–30 breaths/min)
Timestamp	"DD-MM-YYY HH:MIN" TimeStamp	02-02-2019 00:00 and 06-01-2019 00:00
Amenity circumstances (temperature room) (Amb)	All Numeric	Hot Normal Cold
A current activity and a previous one (L_Act and Act)	All Numeric	Eating Sleeping Household Walking Resting

		Exercising
Symptoms (Symp)	All Numeric	0–62
Class	Numeric/Categorical	Emergency Warning Normal Alert
Medication (Med)	Boolean Value	True (Taken) / False (Not Taken)

3.3.2. Setup of the Experiment Environment

All tests were carried out on the same computer system with 8 GB of memory, which has an Intel Core i3 with a clock speed of 2 GHz. The software environment consists of version 3.7.7 with required Python packages for machine learning, data mining, data visualisation, and mathematical calculations. Graphics drivers are set up in a 64-bit version of Microsoft Windows 10. The implementation of the models works based on Google TensorFlow and Keras (Keras Documentation). It's an open-source software package designed to facilitate the design and training of machine learning (ML) models going from simple neural networks to high-level deep learning (DL). Due to the possibility of working with very complicated nonlinear systems, DL is the best and one of the robust learning models available today.

For example, Matplotlib, Seaborn (0.9.1), Google TensorFlow (1.11.1), Pandas (0.23.4), NumPy (1.16.2), SciPy(1.1.0), Scikit-Learn (0.20.1), and Keras (2.2.4) were utilized to build the models (3.0.2). The development and deployment of LPM at Layer 2 is in local environments. The model located in Layer 4, in the cloud platform, is built and deployed using GCP resources cloud masters of labour welfare [48-49].

Core Technologies Used in SPMR:

- **IoT Sensors**: IoT Sensors gather vital patient info and environmental values such as blood pressure, temperature and heart rate.
- **Cloud Platforms (GCP)**: Using Google Cloud Platform is suitable for data storage that expands as required, preparing models and performing analytics in real-time.

- **Machine Learning Algorithms**: The algorithms used are MLPs, CNNs and RNNs. All of them are optimized with the use of CCE.

3.3.3. Key Benefits of the Proposed SPMR Framework

- The system notifies healthcare providers right away when patient status changes, so care can be given faster.
- Automated classification and prediction allow healthcare workers to stop watching patients carefully, as the machine does this job continuously.
- By adding both medical data and the context of activity and surroundings to the model, the predictions become both more accurate and significant.
- Even when the cloud is down, the system can track the environment and act offline from a local source.
- All sensitive patient details are encrypted and only those permitted by access control measures can see them.

3.4.Chapter Summary

The chapter presents the Smart Patient Monitoring and Recommendation (SPMR) framework, which brings together AI, IoT, DL, and cloud computing for real-time monitoring of patient health. It describes a four-layer architecture-AAL, LIP, CMM, and CAM-functioning to support data collection, processing, and predictive modeling. The framework differentiates one for the accurate forecast of the state of health by employing advanced DL methodologies such as the Lifestyle Prediction Mechanism (LPM) and Cloud Predictive Models (CPM). Security procedures, experimental setups, and methods for collecting data are also discussed, emphasizing the SPMR capability for personalized and efficient healthcare management.

Chapter 4: Performance Evaluation of the Proposed Real-Time Vital Sign Monitoring System

Overview

In this chapter, an evaluation of the Smart Patient Monitoring and Recommendation (SPMR) framework efficiency will be unveiled. It opens with an introduction to using deep learning models for patient state classification and prognosis, which helps notify healthcare providers and support agencies. The analysis provides a comparative performance evaluation of local and cloud-based deep learning models and offers a consolidated evaluation against other classifiers in relevant works. Different optimization techniques in improving SPMR's performance are examined, including optimization methods, feature engineering, data augmentation, ensemble models, dynamic updating of models, adaptive thresholds with external data source integration, continuous monitoring, and assessment.

4.1. Introduction

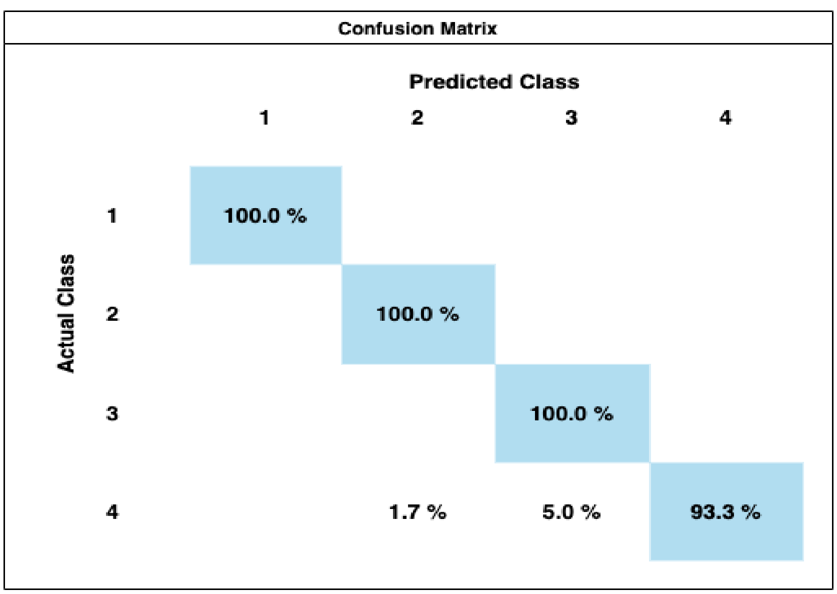
To assess the performance status of the models suggested for SPMR purposes, numerous simulations were performed with diverse optimization setups. Classifying and forecasting the patient's status using the DL and CCE-based model in layer 2 keeps the doctors, carers, and assistance agencies notified [50-52]. Layer 4's CPM utilizes DL and performs similar duties as LPM. The work should be allowed to cover the performance comparison of both respects to each other for the successful identification of the patient's health state for proper recommendations for the patient. Therefore, this comparison covers both local and cloud-based models [53-58].

Comparison of DL+CCE with other classifiers developed in denomination or contemporary works is also present (see Table 10) [59-61]. The confusion matrix serves as the primary source of almost all data-mining parameters. Figs. 14a-c shows the CPM confusion matrix over cloud obtained for three patients on account of multiple classes addressed.

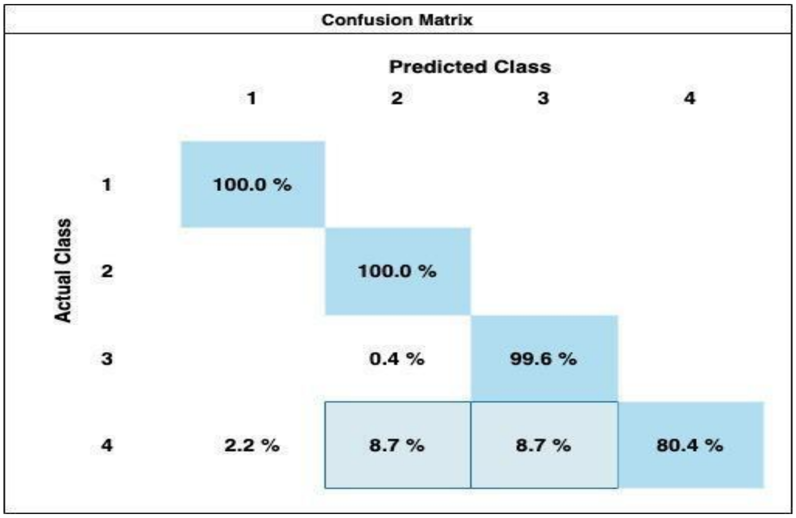
Table 10. A comparison of this research to another recent study.

Ref	Experiment data	Findings	Results

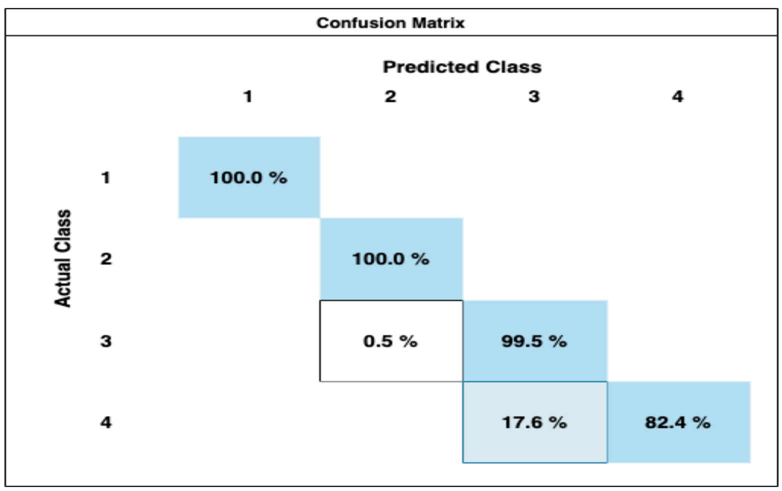
[1]	Neural network design, hybrid logistic regression, feature extraction, and watermark embedding	Chronic Kidney disease factors	Accuracy = 97%
[8]	DecisionTree ANN, SVM, and Ensemble are all examples of machine learning techniques.	Data on physiology and context	Accuracy = 92%
[14]	Perceptron with Multiple Layers (MLP)	Vital statistics Monitoring the context with AAL systems	Accuracy on average = 92.58 percent FPR for P1 equals 0.117; FPR for P2 equals 0.025; and FPR for P3 equals 0.095.
[20]	Methods of sampling; Ensemble; Nave Bayes (NB) + SMOTE; SVM + SMOTE	Data on vital signs in context	Accuracy of NB + SMOTE = 92.5 percent Accuracy of SVM + SMOTE = 84.4 percent
[21]	One-class support vector machine (OCSVM)	Vital parameter sign Monitoring of the ECG	Accuracy = 91%
This study	Deep learning prediction Optimization of categorical cross entropy in a novel way	AAL systems collect vital signs and patient context data.	F-score (Emergency) = 0.91–0.97 DL + Novel CCE (patient side): Accuracy = 99.93% Accuracy = 99.96% F-score (Emergency) = 0.9–0.97



(a)



(b)



(c)

Figure 14. (a) Confusion matrix generated by Cloud Predictive Modeling (CPM) for an individual with hypertension (P1), (b) Confusion matrix for hypotensive patient (P2) and (c) Confusion matrix for a normal patient (P1) (P3)

In seeking avenues to further enhance the performance of the Smart Patient Monitoring and Recommendation (SPMR) framework, several strategies can be explored:

- General techniques of optimization: Engineered to continuously adapt and implement the latest optimization techniques for DL models in the SPMR. Investigating alternative optimization algorithms, or even fine-tuning an existing one, to realize even faster convergences and gains in model performance.
- Feature engineering: Deep feature engineering to find new relevant features that can boost predictions. Investigate contextual features, act of the patient, or life indicators that can provide insight toward health status in general, leading to a more reliable prediction capability of the system.
- Data augmentation: Explore data-augmentation techniques in increasing both dataset size and diversity artificially. The model may be developed further against data imbalance challenges by augmenting the dataset with manipulated instances for further robustness of predictive models.
- Ensemble Models: Investigate ensemble learning techniques that consist of combining multiple models to generate a final prediction. The ensemble model can, at times, outperform its individual counterparts by pooling strengths. Employing an ensemble approach to combine the LPM and CPM together would improve forecasting accuracy.
- Dynamic execution: Build technologies enabling dynamic model updating through continuous learning. The model could be updated instantaneously when new data- on the evolution of patient engagement and healthcare-and a patient-centric model, becomes available.
- Adaptive Thresholds: Investigate the establishment of adaptive thresholds for urgency classifications. Carefully individualize these sensitivity and specificity thresholds based on the pertinent health conditions or characteristics of various patients. This individualization, in turn, will contribute to better and clearer alerting mechanisms other data sources would be considered for integration, including current weather data, air quality data, or another environmental influence for a clearer contextual understanding of a patient's health.
- Ongoing Monitoring and Assessment: Establish meaningful routines or processes for continuous model evaluation and assessments. Develop the modes of feedback loops to enable the system to learn from outcomes and areas of improvement and change over time.

These explorations will help in not only ensuring the highest performance of SPMR but also adapting to the emerging demands in healthcare monitoring, thereby innovating iterative improvements for accuracy, efficiency, and adaptability.

4.2.Performance Metrics

Predictive models are evaluated based on the factors that best identify their predictive models Precision, F-measure, and Categorical Precision are the best metrics for assessment. An essential indicator for model comparison and demonstration of efficacy is the F-score (average) and the F-score of the Emergency class. This F-score is often used to illustrate the efficacy of SPMR in emergency instances. It is the average of the F-scores produced from ten runs of the experiment using test data, which is the F-score (avg.). Only data from the Emergency class is used to calculate an F-score (Emergency).

4.2.1. Accuracy of Prediction: Accuracy of prediction indicates how correctly the system performs. When accuracy is high, most predictions are correct which helps prevent mistakes in clinical monitoring.

$$Accuracy = \frac{True\ results}{Total\ Cases} = \frac{TP + TN}{TP + TN + FP + FN}$$

False Negative, True Positive and False Positive are all abbreviations for the same thing: "True Positive." A comparison of the accuracy of the predictions is provided (see Fig. 15).

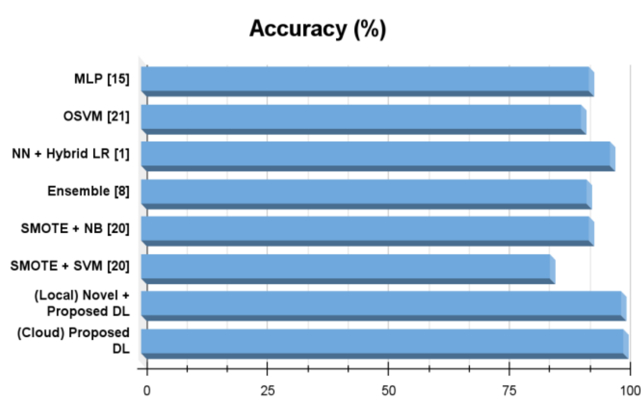


Figure 15. Predictive accuracy is compared against current research.

4.2.2. Representation F-Score

Using the F-score or F1-score, is a way to examine how well the model is predicting on a specific dataset. We are now performing an evaluation of binary classification tools that classify instances as either positive or negative. It is found by averaging how accurate and how many are correctly identified by the model.

- **F-score (Average):** Harmonic mean of precision and recall which helps give a fair measure. It gives useful insight when classes are disproportionate which is typical in healthcare data.

- **F-score (Emergency):** F-score (Emergency) which is vital, tests whether the model is able to detect emergency cases for timely action.

Search engines and various machine learning models, especially in conjunction with natural language processing, are usually rated by means of the F-score.

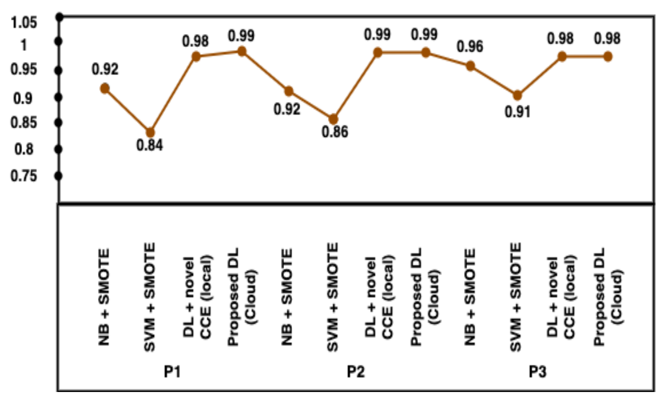


Figure 16. P1, P2, and P3, the average F-score (Average) is compared to work done in the last one year.

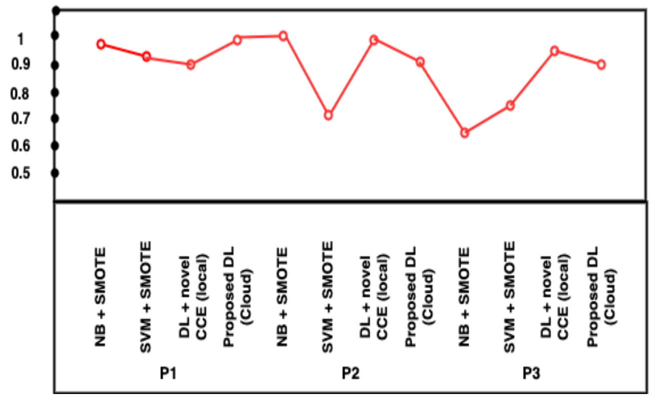


Figure 17. Analysed in comparison to more current work over a period of one year, F-scores for P1, P2, and P3.

Fig. numbers 16 and fig. number 17 represent the mean F-score and the F-score for emergency cases, respectively.

$$F - score = \frac{2 * (Recall * Precision)}{(Recall + Precision)}$$

4.2.3. Representation Of Precision:

True positives among all the times the model predicts positive. It makes fewer false alerts, increasing confidence in alarms among clinicians.

$$Precision = \frac{TP}{TP + FP}$$

4.2.4. Sensitivity/ Recall

The capacity to spot real positive instances. Crucial for not missing any emergency. Statistics uses the term "sensitivity" to mark how accurate a binary classification is. Even so, the idea of "recall" is most commonly related to information engineering.

$$Sensitivity = \frac{TP}{TP + FN}$$

4.2.5. Comparison, Discussion and Results

Integrating Deep Learning (DL) with a novel specific Categorical Cross Entropy (CCE) optimization in SPMR yields remarkable performance and convergence. Proposed SPMR, therefore, has manifestly improved accuracy over all patients compared to existing studies. The sensitivity ranges from 0.79 to 0.93 when looking at alternative models. It is notable that SPMR's Local Predictive Model (LPM) is an outstanding performer in hypertenive individuals, achieving a markedly high F-score (emergency); while the Cloud Predictive Model (CPM) slightly outperforms a bit in hypotensive and normotensive patients. All classifiers achieve an average F-score above 0.90, which is a testament to the ability of SPMR to predict emergencies, alerts, warning signals, and normal occurrences despite data imbalances.

The validation phase of the study carried out on "Smart Patient Monitoring and Recommendation (SPMR) using Cloud Analytics and Deep Learning" encountered a few limitations and constraints along the way. One such limitation involved the long-term monitoring data for patients suffering from chronic diseases, specifically high blood pressure, collected using the Internet of Things (IoT) sensors. There simply is not sufficient data available to create a sound and diverse dataset to train and test the SPMR framework. Moreover, the imbalance in the categories within the database, particularly regarding emergency and alert incidents, affected the performance metrics also. These shortcomings undoubtedly stress the need for further in-depth investigations and data-collection strategies that are all focused on enhancing the robustness and generalizability of the proposed framework to real-world healthcare provision. The validation phase provided an excellent opportunity for identifying these constraints, thus giving a proper basis for improvement and future development in these smart patient monitoring systems. Also, in Table 11 we have added a summary of all above evaluation metrics.

Table 11. SPMR Evaluation Metrics Summary.

Model/Method	Accuracy (%)	F-score (Avg)	F-score (Emergency)	Precision	Recall (Sensitivity)
DL + CCE (SPMR Local - LPM)	99.93	0.94	0.91	High	High

DL + CCE (SPMR Cloud - CPM)	99.96	0.95	0.97	High	High

- To show the effects of the SPMR framework, we have added different clinical impact scenarios from real patient instances. In fact, the system is accurate to 99.96% and can spot changing vital signs as an emergency with a score of 0.97. So, if one of these patients shows signs of trouble, the caregivers would be alerted to take action more quickly. Using these technologies means healthcare staff can focus more on cases that need the most attention.

4.3.Cloud Analytics Infrastructure

In this section, we bring to the open light the very important elements that will comprise the Cloud Analytics Infrastructure platform that is called "Smart Patient Monitoring and Recommendation(SPMR) using Cloud Analytics and Deep learning" in the field of healthcare innovation. This is done with the idea of advancing innovations that over-depend on the advent of Cloud computing facilities ever since. Leveraging the technology of DL and a cloud-based analytical structure, this is a sophisticated platform for real-time prediction and provision of continuous monitoring on the authentic health status of the patient. The incorporation of Categorical Cross Entropy (CCE) Optimization within the DL component emphasizes how this is very much aligned with working rationally so as to gel with real-world health conditions. Most importantly, SPMR will still render real-time preventive measures irrespective of the Sun Surfaces Internet or cloud services being unavailable, streaming information through seamless mode of operations. Comparative analysis vis-a-vis similar setups undoubtedly points to SPMR's model's performance in heightening accuracy along with more improved F-scores. Insightfully, this section gives an insight into taking forward Cloud Analytics Infrastructure of SPMR by showing how practical could being compatible with different platforms and technologies will enrich the newer healthcare monitoring systems.

4.4.Chapter Summary

The chapter assesses the merits of the performance of the SPMR framework through simulations and comparisons with some other models. It describes deeplearning with categorical cross-entropy optimization, having very high accuracy in predicting patient health states and proper recommendations for their timely outflows. Strategies are given for enhancing the performance of the framework, as well as challenges during validation, like data scarcity and unbalanced data sets. The chapter provides a conclusion that mentions the robustness of the SPMR framework, mellowing it down to real-life healthcare situations inherent to its cloud analytics infrastructure.

Chapter 5: Securing Healthcare Infrastructures: Machine Learning Solutions for Healthcare System Integrity

Overview

This chapter investigates HealthGuard, a machine-learning-oriented security solution for Smart Health Systems (SHSs). It begins with an introduction to the ever-expanding importance of health care systems, the background of SHSs and their vulnerabilities, an argument on the problems in scope, an outline of the HealthGuard system, and an evaluation of its performance using different parameters.

5.1. Introduction

As the global population ages and healthcare expenses continue to rise, the need of a reliable healthcare system has become more apparent. Indeed, the most recent estimates indicate that the global healthcare industry's overall expenditure on medical services would reach $53.65 billion by 2025 [1]. More precise diagnoses, more efficient treatments, and technology that improves everyone's quality of life have all been made possible by recent advances in medical technology. Therefore, Medical facilities are becoming ubiquitous and intelligent, owing to the fast development of Internet of Things devices and high-precision medical sensors and applications. More and more, Smart Healthcare Systems, or SHS, are finding uses outside of the traditional healthcare sector. In addition, SHSs include wearable and implanted medical devices that may collect, store, even when the individual in question is not in the hospital, examine a variety of physiological information [2].

By establishing connections to adjacent devices or the online, SHSs may identify medical concerns sooner or perhaps prevent them [3]. This includes gadgets like activity trackers, glucose monitors, wristwatches, and more. Healthcare providers might therefore benefit from SHSs in meeting the rising demand for healthcare systems that are more effective and error-free.

Despite SHSs provide several advantages because to advancements in technology, they are also vulnerable to many cyber threats. One reason is that healthcare statistics tend to be more more comprehensive compared to those regarding other industries, like retail or finance. An illustration of a security issue is the need to disable the wireless pacemaker of an individual connectivity in order to avoid attackers [4]. Academic research has shown many cyber attacks against commercially available implanted cardiac defibrillators (ICDs) and IMDs [5]. An intruder with access to an IMD or ICD might compromise medical operations or alter current ones. Finding a happy medium between privacy, usability, and security could be challenging in the healthcare sector. Any problem with someone's trustworthiness has to be dealt with swiftly and firmly due to the possibly fatal consequences.

Researches in information security, makers of medical devices, and regulatory authorities must, therefore, immediately devote their whole focus to this matter. No comprehensive, uniform method to protect SHSs against harmful assaults has been proposed, despite the researchers' best efforts [6]. To combat these growing threats and SHS shortcomings, this research introduces HealthGuard, a novel security architecture that can detect malicious behavior in a SHS. We built our framework on the premise that a certain collection of medical devices has to be updated for every alteration in a patient's bodily functions. For a complete picture of the patient's health, HealthGuard keeps tabs on all of the SHS devices separately and compares their vital signs. In order to differentiate between healthy and diseased states, HealthGuard may also make use of other biological activities. To find malicious actions in a SHS, HealthGuard uses a number of detection techniques based on Machine Learning (ML). In order to train HealthGuard, an AI system, eight smart medical technologies and twelve innocuous activities were used. Furthermore, HealthGuard was subjected to three distinct assault types. Using an F1-score of 90% and an accuracy of 91%, HealthGuard was able to successfully detect dangerous activities in a SHS.

Research Contributions: We have made a difference in three ways:

- This chapter introduces HealthGuard is a computerized learning-based security of data solution to identify risks related to SHS. The authors of this research created HealthGuard. HealthGuard may detect hazardous behaviors in a (SHS) smart healthcare system by analyzing the relationship between tracking the vital signs and a patient's distinct bodily functions from different smart medical equipment. This is crucial for the detection of detrimental actions.

- A total of nine databases and twelve safe exercises were utilized in HealthGuard's training. The acts consisted of seven behaviors that are typical of users and five behaviors that are linked to disorders.
- We tested the performance of HealthGuard by exposing it to three distinct threats.
- Our comprehensive investigation reveals that HealthGuard exhibits a high degree of precision and achieves an F1 score in detecting various threats to the intelligent healthcare system.

5.2.Background

In this part, we give a brief introduction to a self-healing system (SHS) and go over the many design suppositions and considerations that we have made.

5.2.1. A Smart, Networked Healthcare System

A single device for healthcare or a system (SHS) of devices that employ several sensors to collect information about a patient's body and environment are referred to as smart health systems. Then, using this data, therapy decisions are made on their own.

Integrating wired or wireless technology to promote the sharing of data and information between individuals and medical professionals may benefit the healthcare system in a number of ways. These benefits include improved availability of therapy, enhanced care quality, and increased overall effectiveness of the system. Examples of such technologies are Zigbee and Bluetooth. The intelligent healthcare system may include various intelligent medical devices, including wearable technology, wireless technology, implantable gadgets, as well as others. Our study focuses on self-heating systems (SHS) across a range of devices.

SHS considers not just the aforementioned instruments, but also other additional non-medical aspects, like the patient's geographical location and physical state. To accurately forecast the outcome of an issue (such as a sickness or physiological condition). At this location, the devices gather a range of crucial measurements from the patient to give a thorough assessment of their health. Figure 17 illustrates the process of collecting, examining, and converting essential physiological measurements into digital format. This process occurs in order to get them ready to be sent to a Central Data Processing Unit (CDPU) via network packets [16]. The CDPU utilizes data sent by intelligent medical devices to track patients' overall well-being and promptly alerts clinicians in case of a medical crisis. CDPU has the authority to use independent judgment in some situations, such as determining whether to suggest a new drug or modify a patient's dose. The patient's heart and brain activity are tracked in Figure 18 using an EEG and a cardiac rhythm monitor, respectively. If the patient's health or condition changes, the ECG and electrical brain wave patterns will also alter. Observing a change in the ECG or EEG signal by a medical professional might potentially suggest the presence of cardiac issues. In addition, SHS has the capability to identify and manage a range of predetermined conditions (such as atrial issues, myocardial infarction, etc.) without human intervention.

5.2.2. Multisystem Involvement in Healthcare Analysis

Whenever one organ isn't working adequately, it could have been possible a cascading impact on the whole functioning of the body [17]. An abrupt increase in heart rate may result in symptoms such as palpitations, breathlessness, and potential impairments in the functioning of other organs. Due to the ability of SHS to monitor many biological processes at the same time, any dependency between these processes may be identified and used as a characteristic for diagnosing the problem. The interconnectedness of body function is considered a characteristic for detecting aberrant behavior in SHS. Examples of among the risk factors for cardiovascular disease include sedentary lifestyles, tobacco use, and high blood pressure. The primary organs of focus are the vascular system, the nervous system, and chronic renal disease. Elevated blood pressure has been associated with sleep apnea, unfavorable drug responses, chronic renal illness, and other diseases [18]. An electroencephalogram (EEG), blood pressure, perspiration, glucose, oxygen, and sleep monitoring data can all be used to validate a patient's high blood pressure.

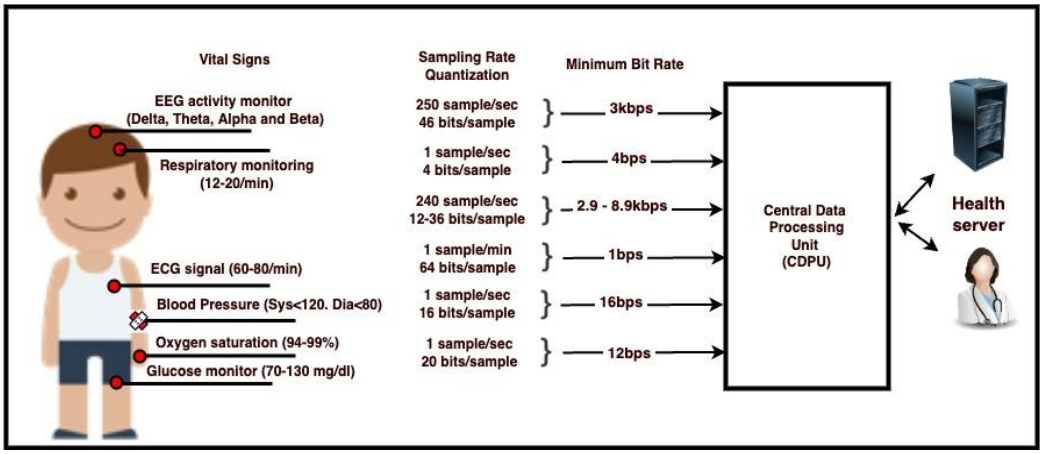


Figure 18. A Prototype of Intelligent Healthcare Framework.

5.2.3. Exploring Deviations in Behavior

In order to detect and categorize abnormal activity, it is essential to first define the criteria for determining what is considered "normal" behavior inside the system. Investigating Anomalous behavioral trends is very compatible with a intelligent architecture for healthcare security due to its ability to identify previously unknown attacks. Obtaining accurate information about typical behavior while minimizing the occurrence of false positives is a major challenge when using an analytical method in a smart home system (SHS). Our proposed answer to this problem is to analyze the devices for abnormal behavior depending on health and activity, with a focus on the patient's needs. During physical exercise, an individual's heart rate rises, oxygen levels decline, breathing rate accelerates, and certain brain waves undergo predictable changes. An effective security framework for a smart home system (SHS) should possess the ability to analyze the vital signs collected by connected smart health devices. By interpreting these vital signs, the framework may determine if the activity is normal or suspicious, based on its knowledge of the ongoing physiological operations of the human body. To understand the harmless acts and identify hazardous situations in a smart home system (SHS), we consider a range of everyday user behaviors and important bodily signs for certain illnesses. For example, a blood pressure monitor will emit a warning if an individual with healthy blood pressure eats meals that are high in cholesterol and the measurement exceeds 120 mm Hg on the systolic side.

By examining user habits and usage patterns, we take into account both the normal as well as disease-affected state of the equipment while building the foundation of HealthGuard.

5.3.Problem scope

At this point we offer an example of use to illustrate the variety of challenges that HealthGuard addresses. Moreover, we outline the several hazards examined by HealthGuard that might potentially pose a threat to SHSs.

5.3.1. Scope of the Problem

To get a perspective on the magnitude of the issue we are dealing with, let's consider a scenario where a (P) patient is brought to the medical facility with a complaint of prolonged chest pain. A secondary school is now under construction, equipped with several intelligent medical devices in order to keep an eye on the patient, essential indicators in case of an outbreak. To evaluate the electrical activity of their brain, P is outfitted with a number of monitoring devices, such as a magnetic resonance imaging (EEG), an oximeter for pulse and an ECG monitor. Furthermore, we assume that the system is entirely impervious to breaches and that no compromised devices have been introduced. Ultimately, the system is set up to quickly notify the physician and administer the necessary medical care in the case of a sudden change in the patient's pulse or rhythm. The electrocardiogram (ECG) ultimately alerted the doctor to the gradual decrease in heart rate irregularities. A brain scan and a device called a pulse oximeter readout, however, show normality, and the patient shows no signs of a change in heart rate.

At this location, we provide HealthGuard, an exceptional framework for security that can evaluate the overall condition of the SHS and determine whether it has been targeted by an assault. HealthGuard effectively addresses many security concerns associated with SHS: (1) Is this warning originating from a solitary intelligent medical gadget, and is it benign or harmful in nature? Does the number (2) indicate the device's alert that indicates the presence of illness? Are there any external factors (natural or man-made) affecting the individual's vital signs? (4) The reliability of a system's pre-established course of operation (such as dispensing a fresh dosage of medicine). By tracking several interrelated patient vitals, our suggested framework may assess the system's overall health. Our technique does not depend just on the outcomes of a single device to assess a patient's well-being. Instead, it considers a diverse array of interconnected indications. HealthGuard can also identify whether the system has been affected by an external source and alert the clinician to halt any possibly dangerous treatment.

5.3.2. Model threat

HealthGuard considers deceptive device behavior that might result in abnormal SHS operation, such as an unauthorized user altering the device's statuses. This part [19] provides a comprehensive analysis of the most severe scenarios that our work may encounter in terms of possible assaults. It considers the attackers' ability to disrupt, tools for disclosing information, and understanding of the system model. An assailant has the capacity to interrupt the functioning and accessibility of a system by interfering with its resources. Additionally, by breaching the system's privacy safeguards during an attack, they could get sensitive information about it. An assailant with a comprehensive comprehension of the system model has the capability to execute intricate assaults. To illustrate the 3 distinct characteristics of the malicious act environment that caught our attention, we selected three distinct assault types.

The paradigm of threat we have includes three instances of fraudulent data injection, two instances of DoS assaults, and one instance of compromised medical equipment. An adversary having prior knowledge of the system and access to disclosure resources may execute a phony data injection attack. A denial-of-service (DoS) attack might only result in disruption to a resource, an assault carried out using compromised technology has the capability to both interrupt the resource and cause harm. For the purpose of simplifying the modeling process, we categorize possible hazards into three distinct classes:

- Firstly, there is the potential for detrimental conduct, whereby an assailant is present and introduces fabricated data to execute malicious actions that modify the patient's physiological condition. There is a risk that false information may be inserted into a medical device [20].
- Furthermore, the installation of a malicious application might potentially introduce dangerous behavior into medical equipment, namely by preventing keeping the gadget from going into a state of sleep. Such a risk is an example of an attack carried out via the use of compromised equipment [21].

- • Thirdly, acts with malicious intent If an assailant were there and able to tamper with any medical gadget nearby, it may momentarily become unworkable. There is a danger of a Denial of Service (DoS) attack [22].

Note: HealthGuard unquestionably offers no defense against passive threats like packet collection or eavesdropping. We are also positive that the SHS data is secure.

5.4.Introduction to the System Architecture

We give a brief introduction of HealthGuard here. HealthGuard's 4 primary parts are as follows: The system is made up of four parts: the first part is in charge of gathering data, the second part preprocesses the data, the third part finds abnormalities, and the fourth part controls actions. These components are represented in Figure 19. Information is gathered by the information collector module from a variety of advanced medical devices. Each of the devices in this collection offers data on a different aspect of the person's vital indicators.

These disparate pieces of information are combined in the information compilation module to create a single array that depicts the patient's current state. To determine whether malicious activity is present inside the SHS, the detect anomalies module makes use of the array produced by the data preparation module.

Finally, the hazardous behavior of the SHS is reported to the appropriate staff using the action management module. Below, you will find information on these parts.

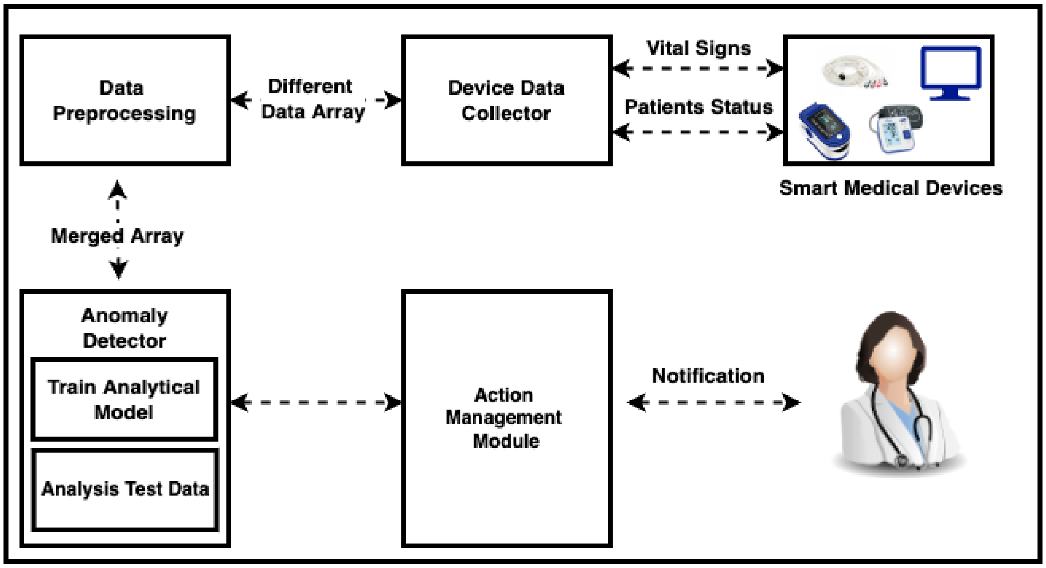


Figure 19. A diagram representing smart healthcare system example

5.4.1. Module is being used to Collect Data

Data from many SHS medical devices is collected using the information module collector. A Smart Home System (SHS) allows for the networking and synchronized operation of several devices. The data collector module utilizes these sensors to aggregate details about the patient and securely keep it in a database system. Considering the data collected by all devices, the above equation may be utilized to describe the material acquired from each device:

$$\text{Data of Device, } A = E1, E2, E3, \ldots. En \tag{1}$$

The set of device features chosen at time t1 is represented by E1, a group of device characteristics chosen at period t2 by E2, and so on. The information purification module receives a variety of data from each device for testing and integration with other data.

5.4.2. Cleansing and Structuring Data

To create a dataset with a variety of characteristics and combine them into a single array, the information collector module sends the information gathered to the cleaning of data module. To give a comprehensive picture of a patient's health, the data gathering module compiles readings from many sources. When integrating data, certain health metrics and evidence are taken into account.

Samples are collected at the appropriate pace for each unique medical equipment by the data preprocessing algorithm. An individual's heart rate can be measured in beats per minute using a heart rate monitor. An electrocardiogram (ECG) monitor, however, measures a patient's heart rhythm and rate every ten seconds. The data compilation module creates just one array from different devices by combining the data samples, which are frequently per-minute data. The data array serves as a temporary log of a SHS's (Solar Home System) overall performance. This collection may be stated mathematically as:

$$\text{Array of Data, } D = \{Dev1, Dev2, Dev3, \ldots\ldots\ldots\ldots Devn\} \quad (2)$$

where Dev1, Dev2, ..., Devn is the collection of information collected from Device1, Device2, ..., on a minute-by-minute basis. After that, the anomaly detection module receives the data array and uses it to train the statistical model that will detect dangerous conditions in the SHS.

5.4.3. Module for Identifying Irregularities

The data palettes produced by the preceding module might be used by the detection of anomaly module to train various algorithms for machine learning (ML) that could identify anomalous activity inside the SHS.

When deciding on ML methods for HeatlhGuard, we took into account two factors: quick computation/detection and straightforward use. Because delays in anomaly identification might have catastrophic consequences for patients, minimizing computation/detection time is crucial. The ML algorithms employed in the anomaly detector must be easy to construct since smart healthcare devices have limited processing capacity. These criteria were met by the Decision Tree (DT), K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), and Random Forest (RF) algorithms, which are also quick to calculate and easy to use [31], [32]. Below, we provide a quick overview of the ML techniques we used and the reasoning behind our decision to use them.

The artificial neural network (ANN) is a computational model developed by scientists to detect anomalies. It is inspired by the structure and operation of real neural networks in the brain. This is done by creating a relationship map that tracks changes in the attributes of a dataset in a manner similar to how biological neurons follow each other [33]. The Multi-layer Perceptron (MLP) approach was used to train the HealthGuard framework since our categorization is multiple-class rather than single and because it is a task requiring supervised learning.

To solve issues of regression and classification, decision trees (DTs) employ a non-parametric modelling strategy. This is done by creating a relationship map that tracks changes in the attributes of a dataset in a manner similar to how biological neurons follow each other [33]. The Multi-layer Perceptron (MLP) approach was used to train the HealthGuard framework since our categorization is multiple-class rather than single and because it is a task requiring supervised learning. Due to the inherent hierarchical structures in the HealthGuard dataset, we conducted extensive testing using a decision tree.

Random Forest (RF): An ensemble classifier that uses a large number of decision trees to construct its models is called a random forest. A randomly chosen subset of the entire training data is used in this instance to train every single tree. For the multi-class classification task [35], we opted for random forest since it provides a more accurate and reliable prediction.

The K-Nearest Neighbors (KNN) algorithm is a form of instance-based learning that remembers just the training examples. On the other hand, it does not produce a unique model for categorising data. Each test sample is assigned to the same class as its nearest neighbor after the gap among every test and training sample is calculated. Because it takes minimal time to train on multi-class data sets, we chose K-nearest neighbor [36].

How non-technical readers can understand ML-based anomaly detection is this: patient data collected from various smart devices is then structured by the system. Using algorithms like Decision Trees, KNN, ANN and Random Forest, computer systems look at the data from health record systems and understand the usual metrics. When they are trained, these models find unusual events or problems that might mean someone is up to something wrong or something is wrong with the system. In case a heart monitor finds an unusual heart rhythm in sleep and doesn’t detect any stress sign, the model highlights it as concerning, relying on brains trained on past data. It reduces the chance of false alarms and detects threats in the moment with context.

5.4.4. Action Processing Module

If any dubious behavior takes place inside the SHS, HealthGuard's action management module will alert the medical staff. HealthGuard stops the automated response to the system's autonomous decisions when it identifies that they are the result of malicious activity, therefore averting undesirable outcomes.

5.5.Evaluation of performance

In the following analysis, we evaluate the efficacy of HealthGuard in detecting malicious behavior inside a SHS (Smart Home System), and determine the feasibility of such detection. In this study, we investigate the efficacy of HealthGuard in preventing attacks by posing a range of research inquiries.

- How well does HealthGuard differentiate between interactions involving sick and healthy users? (See Section 5.5.3)
- How effective is HealthGuard in detecting different types of attacks on Smart Healthcare Systems (SHSs)? (See Section 5.5.4)
- How does the large number of devices in an SHS impact the performance of HealthGuard? (See Section 5.5.5)
- How does the frequency of attacks in an SHS affect HealthGuard's ability to maintain security? (See Section 5.5.6)

5.5.1. **Methodological Framework and Training Environment**

In order to evaluate HealthGuard, data was collected from eight different Internet-connected intelligent medical equipment, including both healthy individuals and those with illnesses.

An individual's blood pressure (BP), electrocardiogram (ECG), blood hemoglobin (HG), oxygen (OX) saturation, neural activity (NA), respiratory rate (BR), sleep (SL), blood alcohol (AL), human motion (HM), and blood glucose (GL) were measured using eight carefully chosen smart medical equipment. We postulated that a human state of good health was characterized by the period including the lowest and greatest values for vital indicators such blood pressure, SpO2 and heart rate. HealthGuard will categorize a person as being within a healthy range if their oxygen saturation has hemoglobin levels among 12.3 as well as 17.5 g/dl and ranges from 94% to 99%. Table 12 presents a concise overview of the devices together with a subset of their pertinent attributes and sources of data. Furthermore, we considered five specific scenarios of disease to provide a comprehensive understanding of how SHS might typically operate in such circumstances. From the selected smart medical devices, we gathered information on blood pressure, cholesterol, sweat rate (SW), oxygen saturation (O2), and glucose levels.

A set of equipment, each specifically intended to identify a certain symptom of a disease, may yield readings that are unusually elevated or reduced, accordingly.

Table 12. Analysis of Devices and Parameters for Monitoring Health Conditions.

Resource List	**Kinds of Device Surveillance**	**Framework**	**Data Source**	**Feature Metric**
[23]	Systolic and Diastolic Pressure & Pulse Rate	Automated Blood Pressure Reader	Fetal ECG Data from Data.Gov	Diastolic (80 mm Hg) and Systolic (120 mm Hg) minutes per beat (60-100)
[24]	O2 Saturation	Smart Oxygen Level Monitor	Exploring the Trends in Oxygen Saturation Variations	Level of SpO2 ≥ 94%
[25]	Glucose Level	MiniMed 670G Insulin Delivery System	UCI Diabetes Classification Data	Blood glucose range of 70 to 130 mg/dL
[26]	Kinetic Activity and Nocturnal Rest	Fitbit Versa Wearable Device	CAP Sleep Patterns Dataset	Stages of Sleep: NREM and REM
[27]	Blood Hemoglobin	Hb Hemoglobin Analyzer by Germaine	Hemoglobin Data from DHS	Between 12.3 and 17.5 g/dl
[28]	Cognitive Activity	Emotiv Insight EEG Device	Event-Related Potential (ERP) and Electroencephalogram (EEG) Data	ERP/EEG data, delta (0.5–4 Hz), alpha (8–12 Hz), theta (4–8 Hz), and beta (16–24 Hz)
[29]	Alcohol Content in Blood	Halt Continuous Alcohol Detection	Dataset from StatCrunch	Eight hundredths of a gram per deciliter
[30]	Breathing and Perspiration Rate	Qardio Heart Monitor	BIDMC PPG and Respiration Monitoring Dataset	Breaths per minute (range 12–20) = 0.5 microns per minute

				per square centimeter

HealthGuard categorizes and recognizes this information as "data influenced by disease," whereas the SHS regards it as usual. Table 13 presents a comprehensive list of disorders along with their corresponding treatment alternatives.

Table 13. Condition of the device in disease-affected environments.

Ref.	NA	BP	HM	SL	SW	OX	HG	BR	GL	AL	ECG	Kind of Disease
[37]	✓	✓	✗	✗	✓	✓	✓	✗	✓	✗	✗	Elevated Cholesterol Levels
[38]	✓	✓	✓	✓	✗	✓	✗	✓	✓	✗	✓	Oxygen Deficiency
[39]	✓	✓	✗	✗	✓	✓	✓	✗	✓	✗	✓	Ab✗rmal Blood Glucose Levels
[40]	✓	✓	✓	✗	✓	✓	✓	✗	✓	✗	✓	Profuse Sweating
[41]	✓	✓	✗	✓	✓	✓	✓	✗	✓	✓	✗	Increased Blood Pressure

The training was done against the backdrop of seven traditional user behaviors; walking, exercise, slumber, stress, drunkenness, heart attack, or stroke. Depending upon the chosen activity, the physiological signals of a group of devices tend to be different [42]. The heart rate will increase; blood sugar levels as well as oxygen levels will drop; sweating rates increase; brain waves will alter for an exercising person. Physiological responses to stress have been shown to consist of increased blood pressure and heart rate, increased breathing and sweating rate, and activation of one specific part of the brain [43]. As these activities don't put the system at risk, and are performed by relatively responsible users, we have labelled them standard SHS activities. A summary of health-imposed user actions under consideration by HealthGuard is provided in the table 14.

Table 14. The state of the device in normal activity situations.

Ref.	NA	AL	HG	HM	SW	OX	BR	GL	BP	ECG	SW	Disease Type
[42]	Yes	No	No	No	Yes	No	Yes	No	Yes	Yes	Yes	Stress
[43]	Yes	No	No	No	No	No	Yes	No	No	Yes	No	Heart-Attack

[44]	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Sleeping
[45]	Yes	No	Yes	Yes	No	No	No	No	Yes	Yes	Yes	Stroke
[46]	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Exercise
[47]	No	Yes	No	No	No	No	Yes	Yes	Yes	No	Yes	Drunk
[48]	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Walking

In order to generate the malevolent dataset, we used the adversary model described in Section 5.3 to replicate three separate assaults on a SHS. Regarding Threat 1, we envisioned a scenario where malicious individuals infiltrate medical devices with fabricated information to execute their assaults.

Our investigation classified a malicious application that disables the sleep function on a smartphone as Threat 2, namely a tampered device assault. We simulated a denial-of-service (DoS) assault on a smart medical device as our third potential threat. We simulated an assault using MATLAB's digital signal processing toolbox and the Poisson distribution. We decide to employ a Poisson distribution to categorize the assault scenarios as uncommon events within a sizable dataset.

We gathered a dataset of 20,000 samples in order to fully evaluate HealthGuard. Of them, seventeen thousand cases involved both healthy and diseased people, while the remaining three thousand instances were data from simulated attacks. The gathered data was split into two equal sections: seventy per cent was utilized to train the design, while the other thirty percent served for testing along with a dataset that contained detrimental components [49].

5.5.2. Metric Performance

The effectiveness of HealthGuard was measured by researchers using the criteria of Precision, Accuracy, F1-score, and Recall.

Although precision indicates the percentage of valid affirmative identifications, accuracy quantifies the extent to which a measured quantity resembles the genuine value of that feature. By computing the recall, one may ascertain the true positive rate. One statistic that takes into account a test's accuracy and recall is the F1-score.

5.5.3. Analysis of activities affected by the disease and those unaffected

Due to certain factors such as user behaviors and the status of the medical person body (e.g., sleeping, exercising, etc.), a person with a Sensory Hyper Sensitivity (SHS) may encounter a range of harmless but infrequent sensations. An effective security system must possess the capability to precisely detect and classify a diverse range of occurrences. HealthGuard's performance in recognizing benign activities was assessed by selecting 7 user behaviors and 5 individuals with the illness conditions that offer medical related data. Table 15 displays the evaluation results for many philanthropic initiatives. The observed accuracy on the F1score scale varies between 90% and 93% across different approaches. By using the DT approach, we achieved a remarkable accuracy rate of 93 percent and obtained the highest attainable F1 score. Ultimately, it is evident that HealthGuard's use of the RF algorithm resulted in the lowest accuracy rate of 89 percent. The K-nearest neighbors (KNN) algorithm has a success rate of 90%, whereas the artificial neural network (ANN) algorithm achieves a higher success rate of 93%. HealthGuard's use of a decision tree algorithm enables it to achieve optimal accuracy and F1 score by effectively identifying non-threatening behaviors.

Table 15. HealthGuard's effectiveness in identifying both benign and harmful incidents in SHS.

	Malicious				**Benign**			
	ANN	**DT**	**RF**	**KNN**	**ANN**	**DT**	**RF**	**KNN**
Recall	0.91	0.91	0.86	0.88	0.93	0.93	0.90	0.90
F1-score	0.89	0.90	0.86	0.87	0.93	0.93	0.90	0.90
Precision	0.90	0.91	0.86	0.88	0.92	0.92	0.90	0.90
Accuracy	0.910	0.909	0.865	0.878	0.927	0.931	0.898	0.903

5.5.4. Testing Under a Number of Attack Conditions

HealthGuard underwent testing in a simulated healthcare setting (SHS) to evaluate its resilience against three primary forms of malicious attacks: tampering with devices, denial-of-service assaults, and the insertion of fabricated data. We conducted a comprehensive evaluation of HealthGuard by using 3000 distinct examples that accurately mirror the typical methods used in attacks. Table 15 shows that, out of all the methods that were studied, the method known as ANN has the best quality (91%) and F1score (89%). It is clear that the F1 score hardly improves (90 percent), while the DT algorithm's accuracy drops to 90%. Both KNN and RF have accuracy and F1 scores that range from 86% to 87%. To put it simply, the ANN algorithm is highly effective in identifying a variety of cyberthreats in SHS.

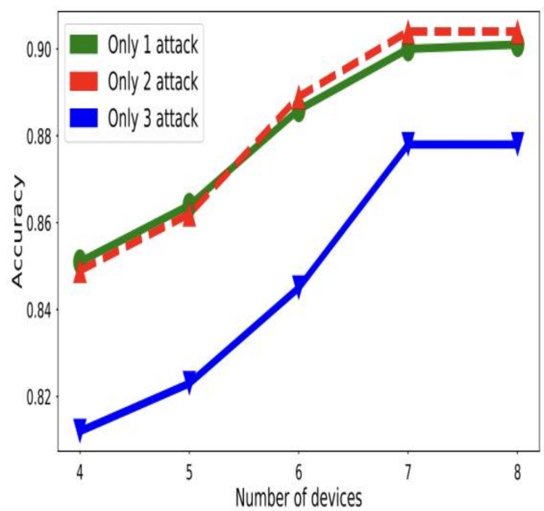
Table 16. Impact of deployment size on HealthGuard's effectiveness.

Device Count	**4**				**5**				**6**				**7**				**8**			
Algo	**Precision**	**F1-score**	**Accuracy**	**Recall**	**Precision**	**F1-score**	**Accuracy**	**Recall**	**Precision**	**F1-score**	**Accuracy**	**Recall**	**Precision**	**F1-score**	**Accuracy**	**Recall**	**Precision**	**F1-score**	**Accuracy**	**Recall**
RF	0.83	0.81	0.839	0.84	0.86	0.85	0.866	0.87	0.91	0.90	0.909	0.91	0.87	0.82	0.851	0.86	0.91	0.90	0.909	0.91
DT	0.78	0.77	0.811	0.81	0.82	0.82	0.861	0.86	0.89	0.89	0.9111	0.91	0.84	0.78	0.832	0.84	0.90	0.89	0.910	0.91
KNN	0.82	0.78	0.812	0.81	0.84	0.83	0.845	0.84	0.88	0.87	0.878	0.88	0.83	0.78	0.831	0.83	0.88	0.87	0.878	0.88
ANN	0.75	0.76	0.772	0.77	0.79	0.79	0.804	0.80	0.86	0.86	0.865	0.86	0.77	0.78	0.777	0.79	0.86	0.86	0.865	0.86

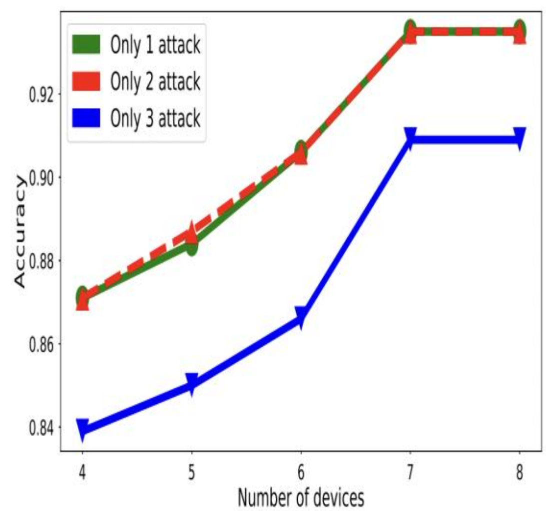
5.5.5. Assessment of Device Count Variations in HealthGuard

A SHS has the capacity to support a diverse range of intelligent medical equipment, enabling thorough monitoring of user or patient conditions. We modified the configuration of SHS and conducted an extensive examination to determine the maximum number of HealthGuard devices that may be connected to it (Table 16). Within the context of SHS, it is evident that there is a negative impact of device count on performance metrics and both accuracy and F1score, wherein an increase in the quantity of devices leads to a reduction in both performance metrics. HealthGuard can more effectively identify events by analyzing a greater number of vital signs obtained from care receiver/end-user related equipment in the SHS. The ranges of F1 scores and accuracy for 8 and 4 connected devices are 77%-89% and 81%-91%, respectively. These results demonstrate that the artificial neural network (ANN) functions well.

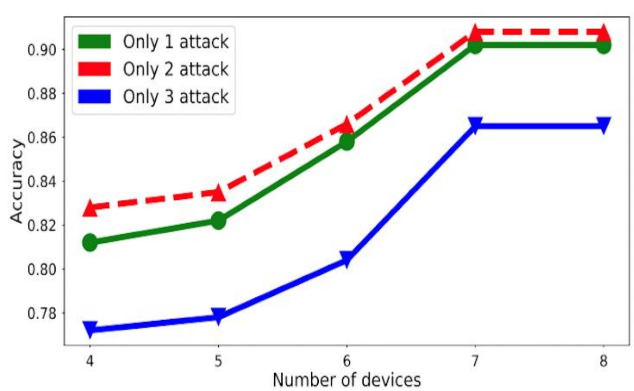
In addition, the decrease in the amount of equipment/devices has a little impact on the F1score and accuracy, with reductions of just 7 percent and 9 percent, respectively. In general, Artificial Neural Network (ANN) attains the maximum F1score and accuracy for HealthGuard. On the other hand, the fewer devices in SHS have a less significant impact on Decision Tree (DT) performance.



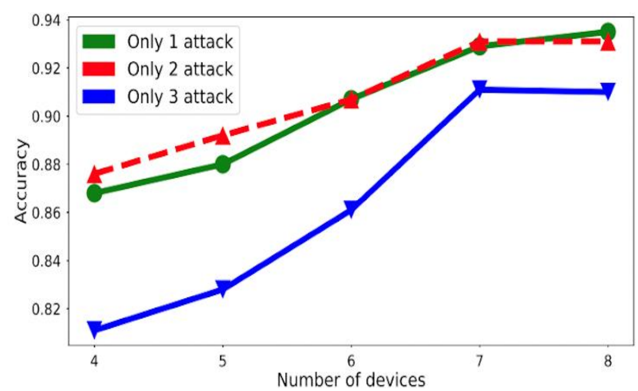
(i) KNN



(ii) DT



(iii) RF



(iv) ANN

Figure 20. Assessing HealthGuard's Performance with Multiple Machine Learning Algorithms

5.5.6. Analyzing HealthGuard Performance in Simultaneous Threat Situations

SHS, multiple coordinated attacks can happen on it in unison. We simulates some attacks on HealthGuard together for the purpose of the test to show how much the system could deal with in term of resistance when subjected to tremendous volumes of attacks. The results of several attacks against the HealthGuard are shown in Fig 20. Each of the detection techniques would be rendered as efficiently as can be based on the fact that there is only one active assault on the system. The accuracy reduces as the number of attacks increases.

Upon comparing at the results from three scenarios (one, two, and three attacks), it appears that ANN always has the highest degree of accuracy. HealthGuard defends against one attack with 93% accuracy, while two and three concurrent attacks are defended against with 95% and 91% accuracy respectively.

5.5.7. Additional Techniques to Enhance Framework Security

While HealthGuard relies on machine learning to discover security issues, extra approaches can improve the security of SHSs:

- Blockchain Integration: By adding a blockchain to the device, changes in patient data and decisions can be checked and verified by others.
- Federated Learning: Federated Learning offers an opportunity for model training across many healthcare nodes without exchanging confidential information which helps preserve privacy and enhances model generalizability.
- Multi-Factor Authentication (MFA): With MFA, SHS administrators are made less vulnerable to unauthorized device control.
- Behavioral Biometrics: Using the way someone acts while using a device such as their typing speed, for consistent authentication.
- Zero Trust Architecture: To use zero trust, verify everything and everyone that requests access, whether they access the network from within or from outside.

As a result, HealthGuard would be able to handle more kinds of cyber threats, as well as new and complex dangers in the digital healthcare field. Because the system uses adaptive threat intelligence, it can detect attacks quickly by understanding and learning from current threats worldwide. Ensuring the use of regulatory compliance modules such as HIPAA and GDPR, will guarantee that your data is properly handled. In addition, protected APIs and containerization help kick out vulnerable parts from accessing the whole system. If HealthGuard has real-time behavioral analysis and sets-up automatic responses, it could catch and block hackers before they can harm patients or sensitive data stored in the system.

5.6. Chapter Summary

In this chapter, HealthGuard introduces a tool with which to fight against the increasing cyber threats plaguing Smart Healthcare Systems (SHSs). The author surveys the basic background on SHS, defines the scope of security challenges to be faced, explains the architecture and components of HealthGuard, evaluates its performance using ML algorithms, and discusses HealthGuard's overall effectiveness in detecting and preventing continuous targeted coherent attacks on Smart Healthcare Systems, accomplishing and attaining a satisfactory level of accuracy of 91% and an F1-score of 90%.

Chapter 6: Conclusion, and Future Directions

Overview

This chapter is the last section of the research work that is explained in the thesis and highlights the major achievements. Furthermore, it outlines the possible directions for the future research of the current study.

6.1. Conclusion

This thesis introduced the Smart Patient Monitoring and Recommendation (SPMR) system as an innovative way to implement real-time health monitoring for patients suffering from chronic diseases, such as hypertension and diabetes. The whole SPMR framework was implemented separately as both self-hosted and cloud-based, also included not only monitoring, but predictive monitoring considering unexpected events such as a loss of power or natural disasters. This feature hugely supports the use of the model when in unexpected and unpredictable scenarios.

The performance of the system was evaluated using Continuous Cross-Entropy optimization for deep learning models that decreased prediction error and functionality, and convergence. Furthermore, the SPMR was deployed in the cloud on Microsoft Azure. Cloud deployment allowed the scaling of cloud infrastructure while information was processed quickly and accurately with large, unstructured health datasets.

The framework provides additional potentially valuable features such as offline learning, which effectively encapsulates both aspects of interoperability and compatibility at a higher level, and it supports storing and processing large data streams, while being resilient in times of low connectivity. Data has well-defined methods and sampling structures that will further support a reduction of overfitting, which is every biomedical modelling problem. Implementation carried out with well-known artificial intelligence frameworks including Scikit-learn, TensorFlow, and Keras that began the process of possible improved implementations and models to be deployed in the future.

Building on the SPMR system, the research enabled the introduction of HealthGuard, a machine learning-based security assurance tool for Smart Healthcare Systems. Testing conducted in hospital wards was successful in achieving a 91% accuracy for threat detection - showing that HealthGuard could fulfill its intended purpose of securing digital healthcare infrastructures - which highlights HealthGuard's real-world applicability. Future work incorporates the integration of IoT and distributed cloud storage systems that will enhance the overall performance of the system, improve the real-time analytics, and improve decision making across the network of care delivery systems.

Despite the significant advances made during this research, certain challenges do deserve mention. The distribution of the data set was imbalanced, with some patients not being represented in these conditions-which led to inconsistencies in the model performance. Furthermore, the initial testing was performed in simulated environments that, while mimicking the relevant clinical environment, controlled and consistent, did not replicate the variability and complexity of real clinical events. Hospital-based permissions have now been obtained, although additional live testing is necessary to validate the system's capability with any reliability in real clinical workflows.

On a personal level, the research process has enhanced my learning on how intelligent systems can enable a technical innovation to be meaningful in human healthcare context. It has emphasized the need to develop solutions that are reliable, adaptable and secure.

In summary, the combined work of the SPMR and HealthGuard systems proposes a proactive methodology in smart healthcare. As the systems continue to improve, there is the opportunity change patient monitoring, improve medical data security, and change the delivery of health care service, either in clinical or remote situations.

6.2. Future Directions

This research work has shown that DL packages such as Scikit-learn, Tensorflow and Keras, allow for the rapid and simple implementation of deep neural networks on local devices. In the future, the framework proposed might serve as a foundation to design different algorithms for deep learning. The context aware framework presented will be applied to other chronic diseases such as cancer. As cited in references [52-57], the proposed framework will be evaluated against research criteria on QoS, energy consumption, and SNS in the cloud.

References:

[1]. Batool, I. (2025). RealTime Health Monitoring Using 5G Networks: A Deep Learning-Based Architecture for Remote Patient Care. arXiv preprint arXiv:2501.01027.

[2]. Liyakat, K. K. S. (2025). Heart health monitoring using IoT and machine learning methods. In AI-Powered Advances in Pharmacology (pp. 257-282). IGI Global.

[3]. Bai, Y., Gu, B., & Tang, C. (2025). Enhancing Real-Time Patient Monitoring in Intensive Care Units with Deep Learning and the Internet of Things. Big Data.

[4]. Arefin, S. (2024). Chronic disease management through an ai-powered application. Journal of Service Science and Management, 17(4), 305-320.

[5]. Heumos, L., Ehmele, P., Treis, T., Upmeier zu Belzen, J., Roellin, E., May, L., ... & Theis, F. J. (2024). An open-source framework for end-to-end analysis of electronic health record data. Nature medicine, 1-12.

[6]. Aisuwarya R, Ferdian R (2019) Monitoring and notifcation system of the position of a person with dementia based on Internet of Things (IoT) and google maps. In: 2019 International Conference on Electrical Engineering and Computer Science (ICECOS). IEEE, New York.

[7]. Ullah, S., Khan, S., Vanecek, D., & Rehman, I. U. (2025). Machine learning and digital-twins-based internet of robotic things for remote patient monitoring. IEEE Access.

[8]. Aldahiri, A., Alrashed, B., & Hussain, W. (2021). Trends in using iot with machine learning in health prediction system. Forecasting, 3(1), 181-206.

[9]. Zhang, S., Sidra, F., Alvarez, C. A., Kinaan, M., Lingvay, I., & Mansi, I. A. (2024). Healthcare utilization, mortality, and cardiovascular events following GLP1-RA initiation in chronic kidney disease. Nature Communications, 15(1), 1-11.

[10]. AlSkaif, T., Bellalta, B., Zapata, M. G., & Ordinas, J. M. B. (2017). Energy efficiency of MAC protocols in low data rate wireless multimedia sensor networks: A comparative study. Ad Hoc Networks, 56, 141-157.

[11]. Bojanova, I., & Samba, A. (2011, March). Analysis of cloud computing delivery architecture models. In 2011 IEEE Workshops of International Conference on Advanced Information Networking and Applications (pp. 453-458). IEEE.

[12]. Chen, H., Jia, X., & Li, H. (2011, October). A brief introduction to IoT gateway. In IET International Conference on Communication Technology and Application (ICCTA 2011) (pp. 610-613). IET.

[13]. Chi, Q., Yan, H., Zhang, C., Pang, Z., & Da Xu, L. (2014). A reconfigurable smart sensor interface for industrial WSN in IoT environment. IEEE transactions on industrial informatics, 10(2), 1417-1425.

[14]. Fehling, C., Leymann, F., Mietzner, R., & Schupeck, W. (2011). A collection of patterns for cloud types, cloud service models, and cloud-based application architectures. University of Stuttgart, Faculty of Computer Science, Electrical Engineering, and Information Technology, Germany, University of Stuttgart, Institute of Architecture of Application Systems, Technical Report Computer Science, 5, 19.

[15]. Ghosh, R., Trivedi, K. S., Naik, V. K., & Kim, D. S. (2010, December). End-to-end performability analysis for infrastructure-as-a-service cloud: An interacting stochastic models approach. In 2010 IEEE 16th Pacific Rim International Symposium on Dependable Computing (pp. 125-132). IEEE.

[16]. Gokhale, P., Bhat, O., & Bhat, S. (2018). Introduction to IOT. International Advanced Research Journal in Science, Engineering and Technology, 5(1), 41-44.

[17]. Hackmann, G., Guo, W., Yan, G., Sun, Z., Lu, C., & Dyke, S. (2013). Cyber-physical codesign of distributed structural health monitoring with wireless sensor networks. IEEE Transactions on Parallel and Distributed Systems, 25(1), 63-72.

[18]. Badriyah, T., Briggs, J. S., Meredith, P., Jarvis, S. W., Schmidt, P. E., Featherstone, P. I., ... & Smith, G. B. (2014). Decision-tree early warning score (DTEWS) validates the design of the National Early Warning Score (NEWS). Resuscitation, 85(3), 418-423.

[19]. Chen, L., Ogundele, O., Clermont, G., Hravnak, M., Pinsky, M. R., & Dubrawski, A. W. (2017). Dynamic and personalized risk forecast in step-down units. Implications for monitoring paradigms. Annals of the American Thoracic Society, 14(3), 384-391.

[20]. Churpek, M. M., Adhikari, R., & Edelson, D. P. (2016). The value of vital sign trends for detecting clinical deterioration on the wards. Resuscitation, 102, 1-5.

[21]. Chiew, C. J., Liu, N., Tagami, T., Wong, T. H., Koh, Z. X., & Ong, M. E. (2019). Heart rate variability based machine learning models for risk prediction of suspected sepsis patients in the emergency department. Medicine, 98(6).

[22]. Chiu, Y. D., Villar, S. S., Brand, J. W., Patteril, M. V., Morrice, D. J., Clayton, J., & Mackay, J. H. (2020). Logistic early warning scores to predict death, cardiac arrest or unplanned intensive care unit re-admission after cardiac surgery. Anaesthesia, 75(2), 162-170.

[23]. Clifton, L., Clifton, D. A., Pimentel, M. A., Watkinson, P. J., & Tarassenko, L. (2013). Predictive monitoring of mobile patients by combining clinical observations with data from wearable sensors. IEEE journal of biomedical and health informatics, 18(3), 722-730.

[24]. Desautels, T., Calvert, J., Hoffman, J., Jay, M., Kerem, Y., Shieh, L., ... & Das, R. (2016). Prediction of sepsis in the intensive care unit with minimal electronic health record data: a machine learning approach. JMIR medical informatics, 4(3), e5909.

[25]. Forkan, A. R. M., & Khalil, I. (2017). A clinical decision-making mechanism for context-aware and patient-specific remote monitoring systems using the correlations of multiple vital signs. Computer methods and programs in biomedicine, 139, 1-16.

[26]. Forkan, A. R. M., & Khalil, I. (2017). PEACE-Home: Probabilistic estimation of abnormal clinical events using vital sign correlations for reliable home-based monitoring. Pervasive and Mobile Computing, 38, 296-311.

[27]. Forkan, A. R. M., Khalil, I., & Atiquzzaman, M. (2017). ViSiBiD: A learning model for early discovery and real-time prediction of severe clinical events using vital signs as big data. Computer Networks, 113, 244-257.

[28]. Guillame-Bert, M., Dubrawski, A., Wang, D., Hravnak, M., Clermont, G., & Pinsky, M. R. (2017). Learning temporal rules to forecast instability in continuously monitored patients. Journal of the American Medical Informatics Association, 24(1), 47-53.

[29]. Ho, J. C., & Park, Y. (2017, July). Learning from different perspectives: Robust cardiac arrest prediction via temporal transfer learning. In 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 1672-1675). IEEE.

[30]. Jang, D. H., Kim, J., Jo, Y. H., Lee, J. H., Hwang, J. E., Park, S. M., ... & Chang, H. (2020). Developing neural network models for early detection of cardiac arrest in emergency department. The American journal of emergency medicine, 38(1), 43-49.

[31]. Forkan, A. R. M., & Khalil, I. (2017). A clinical decision-making mechanism for context-aware and patient-specific remote monitoring systems using the correlations of multiple vital signs. Computer methods and programs in biomedicine, 139, 1-16.

[32]. Kwon, J. M., Lee, Y., Lee, Y., Lee, S., & Park, J. (2018). An algorithm based on deep learning for predicting in-hospital cardiac arrest. Journal of the American Heart Association, 7(13), e008678.

[33]. Larburu, N., Artetxe, A., Escolar, V., Lozano, A., & Kerexeta, J. (2018). Artificial intelligence to prevent mobile heart failure patients decompensation in real time: monitoring-based predictive model. Mobile Information Systems, 2018.

[34]. Li, X., & Wang, Y. (2016). Adaptive online monitoring for ICU patients by combining just-in-time learning and principal component analysis. Journal of clinical monitoring and computing, 30(6), 807-820.

[35]. Liu, N., Koh, Z. X., Goh, J., Lin, Z., Haaland, B., Ting, B. P., & Ong, M. E. H. (2014). Prediction of adverse cardiac events in emergency department patients with chest pain using machine learning for variable selection. BMC medical informatics and decision making, 14(1), 1-9.

[36]. Mao, Q., Jay, M., Hoffman, J. L., Calvert, J., Barton, C., Shimabukuro, D., ... & Das, R. (2018). Multicentre validation of a sepsis prediction algorithm using only vital sign data in the emergency department, general ward and ICU. BMJ open, 8(1), e017833.

[37]. Cabitza, F., Rasoini, R., & Gensini, G. F. (2017). Unintended consequences of machine learning in medicine. Jama, 318(6), 517-518.

[38]. Shashikumar, S. P., Stanley, M. D., Sadiq, I., Li, Q., Holder, A., Clifford, G. D., & Nemati, S. (2017). Early sepsis detection in critical care patients using multiscale blood pressure and heart rate dynamics. Journal of electrocardiology, 50(6), 739-743.

[39]. Tarassenko, L., Hann, A., & Young, D. (2022). Integrated monitoring and analysis for early warning of patient deterioration. BJA: British Journal of Anaesthesia, 97(1), 64-68.

[40]. Van Wyk, F., Khojandi, A., Kamaleswaran, R., Akbilgic, O., Nemati, S., & Davis, R. L. (2017, November). How much data should we collect? A case study in sepsis detection using deep learning. In 2017 IEEE Healthcare Innovations and Point of Care Technologies (HI-POCT) (pp. 109-112). IEEE.

[41]. Yoon, J. H., Mu, L., Chen, L., Dubrawski, A., Hravnak, M., Pinsky, M. R., & Clermont, G. (2019). Predicting tachycardia as a surrogate for instability in the intensive care unit. Journal of Clinical Monitoring and Computing, 33(6), 973-985.

[42]. Barfod, C., Lauritzen, M. M. P., Danker, J. K., Sölétormos, G., Forberg, J. L., Berlac, P. A., ... & Lange, K. H. W. (2012). Abnormal vital signs are strong predictors for intensive care unit admission and in-hospital mortality in adults triaged in the emergency department-a prospective cohort study. Scandinavian journal of trauma, resuscitation and emergency medicine, 20(1), 1-10.

[43]. Hillman, K. M., Bristow, P. J., Chey, T., Daffurn, K., Jacques, T., Norman, S. L., ... & Simmons, G. (2021). Antecedents to hospital deaths. Internal medicine journal, 31(6), 343-348.

[44]. McGaughey, J., Alderdice, F., Fowler, R., Kapila, A., Mayhew, A., & Moutray, M. (2007). Outreach and Early Warning Systems (EWS) for the prevention of intensive care admission and death of critically ill adult patients on general hospital wards. Cochrane Database of Systematic Reviews, (3).

[45]. Gao, H., McDonnell, A., Harrison, D. A., Moore, T., Adam, S., Daly, K., ... & Harvey, S. (2018). Systematic review and evaluation of physiological track and trigger warning systems for identifying at-risk patients on the ward. Intensive care medicine, 33(4), 667-679.

[46]. Cecchinel C, Jimenez M, Mosser S, Riveill M (2014) An architecture to support the collection of big data in the internet of things. In: 2014 IEEE World congress on services, pp 442–449

[47]. Chen M, Li W, Hao Y, Qian Y, Humar I (2018) Edge cognitive com- puting based smart healthcare system. Future Gener Comput Syst 86:403–411

[48]. Chok NS (2010) Pearson's versus Spearman's and Kendall's corre- lation coefficients for continuous data. University of Pittsburgh, Pittsburgh

[49]. Collins GS, Omar O, Shanyinde M, Yu L-M (2013) A systematic review finds prediction models for chronic kidney disease were poorly reported and often developed using inappropriate methods. J Clin Epidemiol 66:268–277

[50]. Das SK, Cook DJ (2005) Designing smart environments: a paradigm based on learning and prediction. In: International conference on pattern recognition and machine intelligence. Springer, pp 80–90 Echouffo-Tcheugui JB, Kengne AP (2012) Risk models to predict chronic kidney disease and its progression: a systematic review. PLOS Med 9:e1001344

[51]. Forkan A, Khalil I, Tari Z (2014) CoCaMAAL: a cloud-oriented con- text-aware middleware in ambient assisted living. Future Gener Comput Syst 35:114–127

[52]. Forkan ARM, Khalil I, Ibaida A, Tari Z (2015) BDCaM: Big data for context-aware monitoring—A personalized knowledge discovery framework for assisted healthcare. IEEE Trans Cloud Comput 5:628–641

[53]. Fortino G, Giannantonio R, Gravina R, Kuryloski P, Jafari R (2012) Enabling effective programming and flexible management of effi- cient body sensor network applications. IEEE Trans Hum Mach Syst 43:115–133

[54]. Garbhapu VV, Gopalan S (2017) IoT based low-cost single sensor node remote health monitoring system. Procedia Comput Sci 113:408–415

[55]. González-Valenzuela S, Liang X, Cao H, Chen M, Leung VC (2012) Body area networks autonomous sensor networks. Springer, Ber- lin, pp 17–37

[56]. Gope P, Hwang T (2015) BSN-Care: a secure IoT-based modern health- care system using body sensor network. IEEE J Biomed Health Inform 16:1368–1376.

[57]. Hämäläinen M, Li X (2017) Recent advances in body area network technology and applications. Int J Wirel Inf Netw 24:63–64

[58]. Hassan MK, El Desouky AI, Elghamrawy SM, Sarhan AM, Engineer- ing E (2018) Intelligent hybrid remote patient-monitoring model with cloud-based framework for knowledge discovery. Comput Electr Eng 70:1034–1048

[59]. Hossain MS, Muhammad GJ (2016) Cloud-assisted industrial internet of things (iiot)-enabled framework for health monitoring. Comput Netw 101:192–202

[60]. Jauch EC et al (2010) Part 11: adult stroke: 2010 American Heart Association guidelines for cardiopulmonary resuscitation and emergency cardiovascular care. Circulation 122:S818–S828

[61]. Jensen D (2019) Beginning Azure IoT edge computing: extending the cloud to the intelligent edge. Apress, Berkeley, CA. https://doi. org/10.1007/978-1-4842-4536-1

[62]. Keras documentation. https://keras.io/

[63]. Kaushar H, Ricchariya P, Motwani A (2014) Comparison of sla based energy efficient dynamic virtual machine consolidation algo- rithms. Int J Comput Appl 102:31–36

[64]. Kohavi R (1995) A study of cross-validation and bootstrap for accuracy estimation and model selection. In: International joint conference on artificial intelligence. vol 2. Montreal, Canada, pp 1137–1145

[65]. Libelium Comunicaciones Distribuidas S.L. (2019) MySignals SW eHealth and Medical IoT development platform technical guide. http://www.libelium.com/downloads/documentation/mysignals_ technical_guide.pdf. Accessed 12 Jan 2020

[66]. Lont M, Milosevic D, van Roermund A (2014) Wireless body area net- works wake-up receiver based ultra-low-power WBAN. Springer, Berlin, pp 7–28

[67]. Malasinghe LP, Ramzan N, Dahal K (2019) Remote patient monitor- ing: a comprehensive study. J Ambient Intell Humaniz Comput 10:57–76

[68]. Motwani A, Patel V, Patil VM (2015) Power and Qos aware virtual machine consolidation in green cloud data center. Int J Electr Electron Comput Eng 4:93

[69]. Muhammed T, Mehmood R, Albeshri A, Katib I (2018) UbeHealth: a personalized ubiquitous cloud and edge-enabled networked healthcare system for smart cities. IEEE Access 6:32258–32285 Musheer RA, Verma C, Srivastava N (2019) Novel machine learning approach for classification of high-dimensional microarray data. Soft Comput 23:13409–13421

[70]. Nathaniel S, Motwani A, Saxena A (2018) Cloud based predictive model for detection of 'chronic kidney disease' risk. Int J Com- put Sci Eng 6:185–188

[71]. Negra R, Jemili I, Belghith A (2016) Wireless body area networks: applications and technologies. Procedia Comput Sc 83:1274–1281 Nielsen MA (2015) Neural networks and deep learning, vol 25. Determination press San Francisco, CA, USA

[72]. Normandeau K (2013) Beyond volume, variety and velocity is the issue of big data veracity. http://insidebigdata.com/2013/09/12/beyon d-volume-variety-velocity-issue-bigdata-veracity/

[73]. Panagiotakopoulos TC, Lyras DP, Livaditis M, Sgarbas KN, Anastasso- poulos GC, Lymberopoulos DK (2010) A contextual data mining approach toward assisting the treatment of anxiety disorders. IEEE Trans Inf Technol Biomed 14:567–581.

[74]. Qureshi, R., Irfan, M., Ali, H., Khan, A., Nittala, A. S., Ali, S., ... & Alam, T. (2023). Artificial Intelligence and Biosensors in Healthcare and its Clinical Relevance: A Review. IEEE Access.

[75]. Sahoo, S., Kumar, S., Abedin, M. Z., Lim, W. M., & Jakhar, S. K. (2023). Deep learning applications in manufacturing operations: a review of trends and ways forward. Journal of Enterprise Information Management, 36(1), 221-251.

[76]. Wong, J., & Zhang, Q. (2023). Deep Learning of Sparse Patterns in Medical IoT for Efficient Big Data Harnessing. IEEE Access, 11, 25856-25864.

[77]. Marin. Cano. E., Cantallops Mora, M., & Sanchez-Alonso, S. (2023). The power of big data analytics over fake news: A scientometric review of Twitter as a predictive system in healthcare. Technological Forecasting and Social Change, 190, 122386.

[78]. Kumar, S., Lim, W. M., Sivarajah, U., & Kaur, J. (2023). Artificial intelligence and blockchain integration in business: trends from a bibliometric-content analysis. Information Systems Frontiers, 25(2), 871-896.

[79]. Konda, D., Patel, U., Rathi, R., Shah, J., & Chothani, N. (2023). Improving protection of compensated transmission line using IoT enabled adaptive auto reclosing scheme. International Journal of Emerging Electric Power Systems, (0).

[80]. Yang, B., Haala, N., & Dong, Z. (2023). Progress and perspectives of point cloud intelligence. Geo-spatial Information Science, 1-17.

[81]. Faisal, M., Zhang, J., Liagouris, J., Kalavri, V., & Varia, M. (2023, August). TVA: A multi-party computation system for secure and expressive time series analytics. In USENIX Security Symposium. USENIX Association.

[82]. Horani, O. M., Khatibi, A., AL-Soud, A. R., Tham, J., & Al-Adwan, A. S. (2023). Determining the Factors Influencing Business Analytics Adoption at Organizational Level: A Systematic Literature Review. Big Data and Cognitive Computing, 7(3), 125.

[83]. Maruyama, M. H. M., Silveira, L. W., de Oliveira, J. P. M., Gasparini, I., & Maran, V. (2023). Hybrid Recommender System for Educational Resources to the Smart University Campus Domain.

[84]. Kapoor, R., Sleeman IV, W. C., Ghosh, P., & Palta, J. R. (2023). Infrastructure tools to support an effective Radiation Oncology Learning Health System. medRxiv, 2023-06.

[85]. Rathore MM, Ahmad A, Paul A, Wan J, Zhang D (2016) Real-time medical emergency response system: exploiting IoT and big data for public health. J Med Syst 40:283

[86]. Roderick O, Marko N, Sanchez D, Aryasomajula A, Handbook DA (2017) Chapter 18—Data analysis and machine learning effort in healthcare: organization, limitations, and development of an approach. In: Geng H (ed) Internet of things and data analytics handbook. Wiley, pp 295–328. https://doi.org/10.1002/97811 19173601.ch18

[87]. Saeed M et al (2011) Multiparameter intelligent monitoring in intensive care II (MIMIC-II): a public-access intensive care unit database. Crit Care Med 3(39):952

[88]. Sarker VK, Jiang M, Gia TN, Anzanpour A, Rahmani AM, Liljeberg P (2017) Portable multipurpose bio-signal acquisition and wireless streaming device for wearables. In: 2017 IEEE sensors applica- tions symposium (SAS), pp 1–6

[89]. Schriger, D. L. (2012). Approach to the patient with abnormal vital signs. In Goldman's Cecil Medicine (pp. 27-30). WB Saunders.

[90]. Khurshid, M. R., Manzoor, S., Sadiq, T., Hussain, L., Khan, M. S., & Dutta, A. K. (2025). Unveiling diabetes onset: Optimized XGBoost with Bayesian optimization for enhanced prediction. PloS one, 20(1), e0310218.

[91]. Sebastian S, Ray (2015) Development of IoT invasive architecture for complying with health of home. In: Proceedings of I3CS, Shillong, pp 79–83

[92]. Sohraby K, Minoli D, Znati T (2007) Wireless sensor networks: tech- nology, protocols, and applications. John Wiley & Sons, New York

[93]. Stüber GL (2017) Principles of mobile communication. Springer, Berlin Sun G, Chang V, Yang G, Liao D (2018) The cost-efficient deployment of replica servers in virtual content distribution networks for data fusion. Inf Sci 432:495–515

[94]. Wang S-H, Govindaraj VV, Górriz JM, Zhang X, Zhang Y-D (2020a) Covid-19 classification by FGCNet with deep feature fusion from graph convolutional network and convolutional neural network. Inf Fusion 67:208–229

[95]. Wang S-H, Zhang Y-D (2020b) DenseNet-201 based deep neural network with composite learning factor and precomputation for multiple sclerosis classification. ACM Trans Multimed Comput Commun Appl 16:1–19

[96]. World Health Organization (2019a) Global health estimates 2016: disease burden by cause, age, sex, by country and by region, 2000–2016. Geneva, 2018

[97]. World Health Organization (2019b) World health statistics 2019: moni- toring health for the SDGs, sustainable development goals

[98]. Young S, Abdou T, Bener A (2018) Deep super learner: a deep ensemble for classification problems. In: Canadian conference on artifi- cial intelligence. Springer, pp 84–95.

[99]. Sun, Z., Chen, T., Meng, X., Bao, Y., Hu, L., & Zhao, R. (2023). A Critical Review for Trustworthy and Explainable Structural Health Monitoring and Risk Prognosis of Bridges with Human-In-The-Loop. Sustainability, 15(8), 6389.

[100]. Su, L., Xu, Z., Chang, F., Ma, Y., Liu, S., Jiang, H., ... & Long, Y. (2021). Early prediction of mortality, severity, and length of stay in the intensive care unit of sepsis patients based on sepsis 3.0 by machine learning models. Frontiers in Medicine, 8, 664966.

[101]. Mainali, S., & Park, S. (2023). Artificial intelligence and big data science in neurocritical care. Critical Care Clinics, 39(1), 235-242.

[102]. Hong, N., Liu, C., Gao, J., Han, L., Chang, F., Gong, M., & Su, L. (2022). State of the art of machine learning–enabled clinical decision support in intensive care units: literature review. JMIR medical informatics, 10(3), e28781.

[103]. Sundrani, S., Chen, J., Jin, B. T., Abad, Z. S. H., Rajpurkar, P., & Kim, D. (2023). Predicting patient decompensation from continuous physiologic monitoring in the emergency department. NPJ Digital Medicine, 6(1), 60.

[104]. Bose, S. N., Defante, A., Greenstein, J. L., Haddad, G. G., Ryu, J., & Winslow, R. L. (2023). A data-driven model for early prediction of need for invasive mechanical ventilation in pediatric intensive care unit patients. PLoS One, 18(8), e0289763.

[105]. Fan, G., Yang, S., Liu, H., Xu, N., Chen, Y., He, J., ... & Rong, L. (2022). Machine learning-based prediction of prolonged intensive care unit stay for critical patients with spinal cord injury. Spine, 47(9), E390-E398.

[106]. Wu, C. P., & Mathur, P. (2024). Artificial intelligence in critical care. In Artificial Intelligence in Clinical Practice (pp. 137-143). Academic Press.

[107]. Zoodsma, R. S., Bosch, R., Alderliesten, T., Bollen, C. W., Kappen, T. H., Koomen, E., ... & Nijman, J. (2023). Continuous Data-Driven Monitoring in Critical Congenital Heart Disease: Clinical Deterioration Model Development. JMIR cardio, 7(1), e45190.

[108]. Almaghrabi, F. S. A. (2021). Machine learning methods for predicting traumatic injuries outcomes. The University of Manchester (United Kingdom).

[109]. Ali, S., El-Sappagh, S., Ali, F., Imran, M., & Abuhmed, T. (2022). Multitask deep learning for cost-effective prediction of patient's length of stay and readmission state using multimodal physical activity sensory data. IEEE Journal of Biomedical and Health Informatics, 26(12), 5793-5804.

[110]. Ahmed, N. (2023). Graph representation of patient's data in EHR for outcome prediction (Doctoral dissertation, Department of Computer Science, Otto-von-Guericke University).

[111]. Gaies, M., Olive, M. K., Owens, G. E., Charpie, J. R., Zhang, W., Pasquali, S. K., ... & Banerjee, M. (2023). Methods to Enhance Causal Inference for Assessing Impact of Clinical Informatics Platform Implementation. Circulation: Cardiovascular Quality and Outcomes, 16(2), e009277.

[112]. Wang, Y. (2023). AI and Big Data in Health: Boosting Reliability and Efficiency in Predictive Healthcare Models (Doctoral dissertation, University of California, Santa Barbara).

[113]. Ehsani, S. (2018). Application of Machine Learning Techniques for Prognosis of Traumatic Brain Injury Patients in Intensive Care Units.

[114]. van de Water, R., Schmidt, H., Elbers, P., Thoral, P., Arnrich, B., & Rockenschaub, P. (2023). Yet Another ICU Benchmark: A Flexible Multi-Center Framework for Clinical ML. arXiv preprint arXiv:2306.05109.

[115]. Naumann, T. (2018). Leveraging text representations for clinical predictive tasks (Doctoral dissertation, Massachusetts Institute of Technology).

[116]. Ghassemi, M. (2017). Representation learning in multi-dimensional clinical timeseries for risk and event prediction (Doctoral dissertation, Massachusetts Institute of Technology).

[117]. Douthit, B. J., Walden, R. L., Cato, K., Coviak, C. P., Cruz, C., D'Agostino, F., ... & Jeffery, A. D. (2022). Data science trends relevant to nursing practice: a rapid review of the 2020 literature. Applied clinical informatics, 13(01), 161-179.

[118]. Vistisen, Simon T., Alistair EW Johnson, and Thomas WL Scheeren. "Predicting vital sign deterioration with artificial intelligence or machine learning." Journal of clinical monitoring and computing 33, no. 6 (2019): 949-951.

[119]. Chen, Lujie, Artur Dubrawski, Donghan Wang, Madalina Fiterau, Mathieu Guillame-Bert, Eliezer Bose, Ata M. Kaynar et al. "Using supervised machine learning to classify real alerts and artifact in online multi-signal vital sign monitoring data." Critical care medicine 44, no. 7 (2016): e456.

[120]. Bloch, Eli, Tammy Rotem, Jonathan Cohen, Pierre Singer, and Yehudit Aperstein. "Machine learning models for analysis of vital signs dynamics: a case for sepsis onset prediction." Journal of healthcare engineering 2019 (2019).

[121]. Baidillah, Marlin Ramadhan, Pratondo Busono, and Riyanto Riyanto. "Mechanical ventilation intervention based on machine learning from vital signs monitoring: A scoping review." Measurement Science and Technology (2023).

[122]. Tang, Shengpu, Grant T. Chappell, Amanda Mazzoli, Muneesh Tewari, Sung Won Choi, and Jenna Wiens. "Predicting acute graft-versus-host disease using machine learning and longitudinal vital sign data from electronic health records." JCO clinical cancer informatics 4 (2020): 128-135.

[123]. Khan, Muhammad Imran, Mian Ahmad Jan, Yar Muhammad, Dinh-Thuan Do, Ateeq ur Rehman, Constandinos X. Mavromoustakis, and Evangelos Pallis. "Tracking vital signs of a patient using channel state information and machine learning for a smart healthcare system." Neural Computing and Applications (2021): 1-15.

[124]. Liu, Nehemiah T., John B. Holcomb, Charles E. Wade, Mark I. Darrah, and Jose Salinas. "Utility of vital signs, heart rate variability and complexity, and machine learning for identifying the need for lifesaving interventions in trauma patients." Shock 42, no. 2 (2014): 108-114.

[125]. Li-wei, H. Lehman, Roger G. Mark, and Shamim Nemati. "A model-based machine learning approach to probing autonomic regulation from nonstationary vital-sign time series." IEEE journal of biomedical and health informatics 22, no. 1 (2016): 56-66.

[126]. Li-wei, H. Lehman, Shamim Nemati, George B. Moody, Thomas Heldt, and Roger G. Mark. "Uncovering clinical significance of vital sign dynamics in critical care." In Computing in Cardiology 2014, pp. 1141-1144. IEEE, 2014.

[127]. Iyer, Srikrishna, Leo Zhao, Manoj Prabhakar Mohan, Joe Jimeno, Mohammed Yakoob Siyal, Arokiaswami Alphones, and Muhammad Faeyz Karim. "mm-Wave radar-based vital signs monitoring and arrhythmia detection using machine learning." Sensors 22, no. 9 (2022): 3106.

[128]. Rana, Soumya Prakash, Maitreyee Dey, Robert Brown, Hafeez Ur Siddiqui, and Sandra Dudley. "Remote vital sign recognition through machine learning augmented UWB." (2018): 619-5.

[129]. Rajan Jeyaraj, P., & Nadar, E. R. S. (2022). Smart-monitor: patient monitoring system for IoT-based healthcare system using deep learning. IETE Journal of Research, 68(2), 1435-1442.

[130]. Jaber, M. M., Alameri, T., Ali, M. H., Alsyouf, A., Al-Bsheish, M., Aldhmadi, B. K., & Jarrar, M. T. (2022). Remotely monitoring COVID-19 patient health condition using metaheuristics convolute networks from IoT-based wearable device health data. Sensors, 22(3), 1205.

[131]. Malche, T., Tharewal, S., Tiwari, P. K., Jabarulla, M. Y., Alnuaim, A. A., Hatamleh, W. A., & Ullah, M. A. (2022). Artificial Intelligence of Things-(AIoT-) Based Patient Activity Tracking System for Remote Patient Monitoring. Journal of Healthcare Engineering, 2022.

[132]. Aldabbas, H., Albashish, D., Khatatneh, K., & Amin, R. (2022). An architecture of IoT-aware healthcare smart system by leveraging machine learning. Int. Arab J. Inf. Technol., 19(2), 160-172.

[133]. Stone, D., Michalkova, L., & Machova, V. (2022). Machine and Deep Learning Techniques, Body Sensor Networks, and Internet of Things-based Smart Healthcare Systems in COVID-19 Remote Patient Monitoring. American Journal of Medical Research, 9(1), 97-112.

[134]. Woods, M., & Miklencicova, R. (2021). Digital Epidemiological Surveillance, Smart Telemedicine Diagnosis Systems, and Machine Learning-based Real-Time Data Sensing and Processing in COVID-19 Remote Patient Monitoring. American Journal of Medical Research, 8(2), 65-78.

[135]. Garbhapu VV, Gopalan S (2017) IoT based low-cost single sensor node remote health monitoring system. Procedia Comput Sci 113:408–415

[136]. Gope P, Hwang T (2015) BSN-Care: a secure IoT-based modern health- care system using body sensor network. IEEE J Biomed Health Inform 16:1368–1376.

[137]. Castiñeira, D., Schlosser, K. R., Geva, A., Rahmani, A. R., Fiore, G., Walsh, B. K., ... & Santillana, M. (2020). Adding continuous vital sign information to static clinical data improves the prediction of length of stay after intubation: a data-driven machine learning approach. Respiratory care, 65(9), 1367-1377.

[138]. Ruiz, V. M., Goldsmith, M. P., Shi, L., Simpao, A. F., Gálvez, J. A., Naim, M. Y., ... & Tsui, F. R. (2022). Early prediction of clinical deterioration using data-driven machine-learning modeling of electronic health records. The Journal of Thoracic and Cardiovascular Surgery, 164(1), 211-222.

[139]. Yallabandi, G., Mayya, V., Jeganathan, J., & Kamath, S. (2023). ICU Patients' Pattern Recognition and Correlation Identification of Vital Parameters Using Optimized Machine Learning Models. International journal of electrical and computer engineering systems, 14(9), 1003-1013.

[140]. Nguyen, M., Corbin, C. K., Eulalio, T., Ostberg, N. P., Machiraju, G., Marafino, B. J., ... & Chen, J. H. (2021). Developing machine learning models to personalize care levels among emergency room patients for hospital admission. Journal of the American Medical Informatics Association, 28(11), 2423-2432.

[141]. Maldonado Belmonte, E., Oton-Tortosa, S., Gutierrez-Martinez, J. M., & Castillo-Martinez, A. (2024, June). An Intelligent Model and Methodology for Predicting Length of Stay and Survival in a Critical Care Hospital Unit. In Informatics (Vol. 11, No. 2, p. 34). Multidisciplinary Digital Publishing Institute.

[142]. McAdams, R. M., Kaur, R., Sun, Y., Bindra, H., Cho, S. J., & Singh, H. (2022). Predicting clinical outcomes using artificial intelligence and machine learning in neonatal intensive care units: a systematic review. Journal of Perinatology, 42(12), 1561-1575.

[143]. Nong, Y., Kim, J. S., Jia, L., Arancio, O., & Wang, Q. (2025). The interaction between neurotransmitter receptor activity and amyloid-β pathology in Alzheimer's disease. Journal of Alzheimer’s Disease, 13872877251342273.

[144]. Raouf, I., Kumar, P., Cheon, Y., Tanveer, M., Jo, S. H., & Kim, H. S. (2025). Advances in prognostics and health management for aircraft landing gear—progress, challenges, and future possibilities. International Journal of Precision Engineering and Manufacturing-Green Technology, 12(1), 301-320.

[145]. Berry, G. T., Demirbas, D., & Volpe, J. J. (2025). Organic Acids. In Volpe's Neurology of the Newborn (pp. 940-964). Content Repository Only!.

LIST OF PUBLICATIONS

Journals

i. **Sundas, A.,** et al. (2024). Smart Patient Monitoring and Recommendation (SPMR) using Cloud Analytics and Deep Learning. IEEE Access. **(SCI)**

ii. **Sundas, A.,** et al. (2023). Evaluation of autism spectrum disorder based on the healthcare by using artificial intelligence strategies. Journal of Sensors, 2023, 1-12**. (SCI)**

iii. **Sundas, A.,** et al. (2023). Investigating the Role of Machine Learning Algorithms in Predicting Sepsis using Vital Sign Data. International Journal of Advanced Computer Science and Applications, 14(10). **(Scopus)**

iv. **Sundas, A.,** et al. (2022). HealthGuard: An intelligent healthcare system security framework based on machine learning. Sustainability, 14(19), 11934. **(SCI)**

v. **Sundas, A**., et al. (2022). Comprehensive Study of Machine Learning-Based Systems for Early Warning of Clinical Deterioration. International Journal of Performability Engineering, 18(12), 893. **(Scopus)**

Conferences

i. **Sundas, A**., et al. (2023, January). Sensor Data Transforming into Real-Time Healthcare Evaluation: A Review of Internet of Things Healthcare Monitoring Applications. In 2023 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE) (pp. 559-567). IEEE. **(Scopus)**

ii. **Sundas, A**., et al. (2022, October). Recurring Threats to Smart Healthcare Systems Based on Machine Learning. In 2022 10th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO) (pp. 1-8). IEEE. **(Scopus)**

iii. **Sundas, A.,** et al. (2023). Streamlined Patient Care With Smart Monitoring and Deep Learning-based Recommendations Using Categorical Cross Entropy Optimization. Kilby, 100, 7th. **(Scopus)**

iv. **Sundas, A.,** et al. (2023). Internet of Health Things-enabled monitoring of vital signs in hospitals of the future. In First International Conference on Applied Data Science and Smart

Systems, Department of computer application Chitkara University, India. (https://ca.chitkara.edu.in/adsss/). **(Scopus)**.

v. **Sundas, A.,** et al. (2023). Optimizing Length of Stay Prediction After Intubation an Advanced Machine Learning Model with Real-time Vital Sign Integration. In 2023 Seventh International Conference on Image Information Processing (ICIIP -2023), Jaypee University of Information Technology, Waknaghat, District Solan, Near Shimla, Himachal Pradesh, India. (https://www.juit.ac.in/iciip_2023/). **(Scopus)**.

vi. **Sundas, A.,** et al. (2024). Deep Learning-Based IoT Solutions for Real-Time Health Monitoring. In 1st International Conference on Smart Computing and Communication for Sustainable Convergence (ISCCSC2024), Department of computer application Chitkara University, India. (https://www.chitkara.edu.in/icetss/). **(Scopus)**.

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स्त्रीरोग व प्रसुतीशास्त्र तज्ञ
रजि.नं. २००४/०२/५८८

New Aasha Hospital

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वेळ : सकाळी १०.०० ते दुपारी १.०० आणि सायंकाळी ५.०० ते रात्री ८.००

To,
Dr. Swapnil Saitwal
MBBS, MS, DGO, FCPS, DFP
Gynaecologist and Obstetrician
New Aasha Hospital,
Prakash Nager, Jalgaon Road, Jamner

Subject: Request for Approval of Vital Signs for Chronic Illness Detection in Ph.D. Research

Respected Sir,

I hope this letter finds you well. My name is Amit Sundas, and I am currently pursuing a Ph.D. from Lovely Professional University with the registration number 42100013.

The title of my research work is **"A Novel Machine Learning Based Real-Time Vital Sign Monitoring System."**

As part of my research, I aim to develop a system capable of monitoring and analyzing vital signs to identify critical chronic illnesses effectively. I seek your approval to confirm that the following selected vital signs and related factors are sufficient for detecting and identifying such conditions:

Dependent	Independent
Heart Rate (HR)	High Activity and low activity
Peripheral Oxygen Saturation (SpO2)	Ambient conditions (room temperature)
Diastolic Blood Pressure (DBP)	Symptoms
Respiratory Rate (RR)	Medication (Med)
Systolic Blood Pressure (SBP)	
Other Relevant Factors: • Patient age • Patient gender • Patient medical history • Patient physical condition	

I believe that the inclusion of these parameters will provide a comprehensive dataset for analyzing critical health conditions related to chronic illnesses. Your guidance and approval regarding the adequacy of these vital signs and factors for my research would be greatly appreciated.

Please let me know if any additional information or documentation is required. I look forward to your valuable feedback and approval.

Thank you for your time and consideration.

Sincerely,
Amit Sundas
Ph.D. Candidate
Lovely Professional University
Registration Number: 42100013
Mobile number: 9888402304

आशा प्रसुतीगृह
डॉ.स्वप्नील सैतवाल
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