Smart Wearable-based Digital Healthcare System

Submitted By

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

INSTITUTE OF TECHNOLOGY

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Smart Wearable-based Digital Healthcare System

Major Project - II

Submitted in partial fulfillment of the requirements

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Submitted By

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Certificate

This is to certify that the major project entitled **"Smart Wearable-based Digital Healthcare System"** submitted by **Vrutti H Tandel (Roll No: 21MCEC18)**, towards the partial fulfillment of the requirements for the award of degree of Master of Technology in Computer Science and Engineering (Specialization in title case, if applicable) of Nirma University, Ahmedabad, is the record of work carried out by him under my supervision and guidance. In my opinion, the submitted work has reached a level required for being accepted for examination. The results embodied in this major project part-I, to the best of my knowledge, haven't been submitted to any other university or institution for award of any degree or diploma.

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Statement of Originality

I,**Vrutti H Tandel**, Roll. No. **21MCEC18**, give undertaking that the Major Project entitled **"Smart Wearable-based Digital Healthcare System"** submitted by me, towards the partial fulfillment of the requirements for the degree of Master of Technology in **Computer Science & Engineering (*Computer Science and Engineering*)** of Institute of Technology, Nirma University, Ahmedabad, contains no material that has been awarded for any degree or diploma in any university or school in any territory to the best of my knowledge. It is the original work carried out by me and I give assurance that no attempt of plagiarism has been made.It contains no material that is previously published or written, except where reference has been made. I understand that in the event of any similarity found subsequently with any published work or any dissertation work elsewhere; it will result in severe disciplinary action.

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Place:

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Endorsed by
Dr. Aparna Kumari
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Abstract

Over the last few years, the Internet of Things (IoT) has drastically transformed the healthcare industry by enabling real-time monitoring services using smart wearable devices like smartwatches, rings, etc. IoT-based smart wearable devices are changing traditional processes of healthcare to personalized healthcare systems. It enhancing persons daily activities, boosts people's well-being, and transforms our quality of living (QoL). Further, smart wearable devices help in monitoring and improving personalized healthcare by tracking day-to-day activities, where IoT-based sensors collect data from smart wearables and stored in a cloud-based storage system. From the cloud, data is further gathered for analysis. Several research work has been done so far in this regard but it has not been exploited fully. Hence, this study proposed a machine learning (ML)-based digital healthcare system for the precise prediction of daily activities using real-time data. Next, experimental results are evaluated using ML models like Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF) applied for the activity prediction. The proposed approach proved its effectiveness by comparing it with the traditional system with respect to various performance evolution matrices of accuracy, root mean square error (RMSE), mean squared error (MSE), mean absolute error (MAE), and R2 score.

Abbreviations

ML	Machine Learning
RF	Random Forest
SVM	Support Vector Machine
DT	Decision Tree
NB	Naive Bayes
USD	United States Dollar
NCD	Non-communicable disease
RMSE	Root Mean Square Error
MSE	Mean Square Error
MAE	Mean Absolute Error
MET	Metabolic Equation of task
QoL	Quality of Life
IoT	Internet of Things

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Chapter 1

Introduction

Advancing personalised healthcare through smart wearable devices is important. Based on the most recent smart wearable technology the transition of the conventional hospital-based healthcare system to a service-based patient-clinic for personalized healthcare is expanded based on the latest technology of wearable devices [1]. These smart wearable devices are used to record, process, and communicate a broad range of information by lowering the cost, power consumption, and compactness in size. The increase in wearable devices will make a better healthcare system in the future [1] [2].

These wearable devices keep track of things similar to those for oxygen, cholesterol, and calories burned, by their IoT-based sensors. It helps with personal health monitoring. Moreover, many several business companies are introducing smart wearable devices like smartwatches, rings, mouthguards, headsets, and with additional accessories healthcare options for tracking, including Apple watches, Samsung, Fitbit devices, Noise, etc [3]. Consumer growth on smart Wearable devices is fueling business expansion [3].

Wearable devices make real-time analysis and observation practically possible everywhere. Internet of Things (IoT) has established a firm presence in every aspect of our lives [4]. IoT wearable devices have sensors that end users wear to track their activities of health such as body temperature, walking steps, exercise, sleep, and heart rate. Patients and individuals can measure their health activities, such as body temperature, walking steps, exercise, sleep, and heart rate by wearing IoT-based wearable devices. These IoT-based smart wearable devices help to improve personalized healthcare, remote healthcare, and cost savings.

IoT-based smart wearable devices are paired with patients' bodies to monitor their various activities such as heart rate, body temperature, exercise, walking steps, sleep monitoring, etc. As a result, various readings are taken from smart wearable devices to monitor the health status of an individual. Moreover, there are issues and challenges related to the collection of data and managing the wide amount of data collected from IoT-based smart wearable devices and using them for the decision-making process. To deal with a wide range of data, machine learning (ML) algorithms are important for the decision-making process.

1.0.1 Research Contributions

Following are the research contributions of this paper.

- ML-based activity classification model and predict the activity values for different activities.
- Proposed an ML-based activity classification model and predict the activity values for different activities.
- A ML-based based data analytics method is proposed from smart wearable devices to improve personalised healthcare. Designed a system model and proposed architecture to evaluate and improve healthcare.
- A comparative analysis is performed based on various parameters for instance RMSE, MSE, accuracy.

Chapter 2

Literature Survey

2.1 Machine Learning Techniques

To propose an ML-based secure data analytic approach for smart wearable devices in the personalized healthcare domain for the healthcare industry 5.0. The proposed approach will be evaluated by considering different performance analyses, such as accuracy, prediction, precision, scalability, response time, and data security. To propose an ML-based secure data analytic approach for smart wearable devices in the personalized healthcare domain for the healthcare industry 5.0.

2.2 Healthcare Industry

Healthcare Industry 1.0 represents the use of mechanical productions starting from the eighteen century to the mid-nineteen century [18]. The development of steam engines, railways, steel industries, and steam power helped societies, agriculture, and industrialization to transform and develop in the mechanization revolution [19]. Healthcare Industry 1.0 describes the fundamental hospital (clinic) and patient interaction. A patient visits the clinic to meet a doctor and other healthcare teams for a checkup. The clinic consults with the patient conducts tests, diagnoses the disease, and then recommends prescribed medicine. For hundreds of years, this system has been in use for the delivery of healthcare. Due to the excessive use of electric power, mass production, and assembly line production, the new industrial revolution from the mid-eighteenth century to the nineteenth century is also called the Healthcare Industry 2.0 [19]. Multiple new medical tools have been introduced for the diagnosis, monitoring, and treat the healthcare of patients. From

Authors	Year	Objectives	1	2	3	4	5	6	Cons
Sabry et al. [5]	2022	Study of healthcare wearable devices in ML	No	Yes	Yes	Yes	Yes	Yes	challenges faced by ML applications not discussed
Habib et al. [6]	2022	Investigating healthcare system associated between quality of life and depression based on ML	Yes	Yes	No	Yes	Yes	No	the dataset does not require factors according to study.
Chandra et al. [7]	2022	Evolving and progressing nations from: healthcare, covid-19, digital technologies	No	Yes	No	No	Yes	No	Due to massive data size security is needed properly
Brönneke et al. [8]	2021	Highlights cardiac monitoring for market aspects, Legal, and regulatory	No	Yes	Yes	No	No	Yes	missing privacy for software development
kushwaha et al. [9]	2021	Review on ML algorithms based in healthcare	No	Yes	No	No	Yes	No	Result is not accurate on ML techniques
Indrakumari et al. [10]	2020	IoTs exapnding role in healthcare wearable devices	Yes	Yes	Yes	No	Yes	No	Privacy and Security is main issue needs to be resolved in wearable devices
Jahankhani et al. [11]	2019	Discussed about healthcare in digital transformation	Yes	Yes	Yes	No	No	No	Security is missing
Tian et al. [12]	2019	Making medical treatment intelligent with smart healthcare	No	No	No	Yes	No	No	the amount of data is large and complicated, which leads in difficulties and data sharing
Dunn et al. [13]	2018	Reviwed about medical revolution and wearable devices	No	Yes	Yes	No	Yes	No	technical and regulatory hurdles remain
Shailaja el al. [14]	2018	Review of healthcare in ML	No	Yes	No	No	Yes	No	Accuracy for breast cancer is not proper
Muhammad et al. [15]	2018	A customized universal networked healthcare system for smart cities that is supported via the cloud and the edge is called UbeHealth.	No	Yes	No	Yes	Yes	No	Security, Reliability, and latency are missing
Frederic Michard et al. [16]	2017	A closer look at wearable devices and digital innovations for cardiac monitoring sensors	No	Yes	Yes	No	No	No	Quick and efficient process is needed
Chan et al. [17]	2012	Future challenges and current work of smart wearable devices	No	Yes	Yes	Yes	Yes	Yes	Privacy and ethical issues are barrier

Parameters - 1: Taxonomy 2: Artifacts 3: Wearables 4: Research Gaps 5: Applications 6: Case Study the last few years between the mid-nineteenth century and twenty century, the development of programable computers and robotic technologies had led to massive automation system applications by networking and digitalization of production and business operations. Healthcare Industry 3.0 is primarily conducted on-site and is mainly biomedical, and is focused primarily on infectious diseases like covid-19 [20] [18]. As we move on to the 21st century, the healthcare industry aspires to connect to the cyber-physical system [19]. Then, Big data analytics and artificial intelligence methods are utilized in conjunction with IoT and its accompanying services. The size of the data used in healthcare also increases from the small set to big data to various datasets with a range of types, sizes, and variations. Healthcare Industry 4.0 [21] is conducted in multidisciplinary centers and covers broader health issues, including Non-communicable diseases (NCD) and disparities. It includes merging the real-world virtual world based on the physical cyber production system [22] [21] [23] [20]. The final stage of the healthcare industry is Industry 5.0, which flipping the industry operational models by adapting to the needs of customers and recognizing the customer's core role. Industry 5.0 shifting the focus toward "customer-managed relationships" from "customer relationship management".

2.3 Proposed Taxonomy

Figure 2.1 depicts the proposed taxonomy for smart wearable-based healthcare industry 5.0. In this study, we proposed a concise taxonomy, however, the scope of smart wearable devices in Healthcare 5.0 is not limited to this work. In this study, we have done the categorization of the proposed taxonomy into four categories: (i) wearable modes, (ii) health tracking, (iii) security and privacy issues, and (iv) application and services. In wearable modes, different wearable devices have various applications of wearable sensors, such as wristwatches, rings, and headbands. These wearables have different modes such as power mode which is categorized into active mode and passive mode. Furthermore, there is a common mode which will be divided into wired and wireless modes and the last one is deployment mode. The next segment is *Healthcare Tracking* used to record and manage the health of a human being. Healthcare tracking can be further divided into health monitoring and medical resource automation. Health monitoring can be categorized into preventive and responsive one. Various latest technologies like ML, IoT, and others play an important role in healthcare monitoring. ML-based medical service

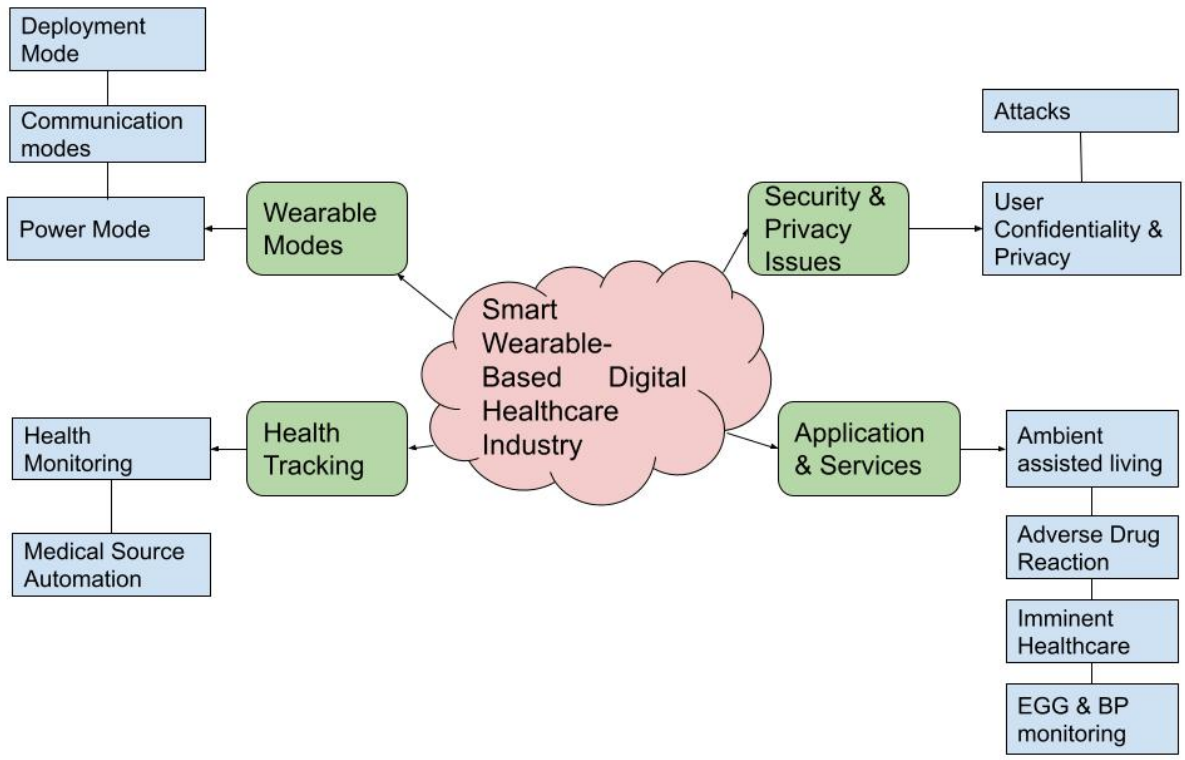

Figure 2.1: The Proposed Taxonomy

automation provides benefits to the end-users and also reduces human effort. ML-based approaches also comprise posture correction and fitness of human beings. The third is the security and privacy issues of wearable devices in healthcare which include attacks & on user confidentiality and privacy. Here, different attacks such as replay attacks, phishing attacks, data modification attacks, man-in-the-middle attacks, jamming, blackhole, data leakage, and Bluetooth attack are discussed in detail along with their prevention mechanism. In the last category, the proposed taxonomy discussed the various application and services in smart wearable devices in Healthcare 5.0.

Table 2.1: Comperative analysis of existing approach

Proposed Approach	**Year**	**Short Description**	**Pros**	**Cons**
Navita *et al.*[24]	2022	Performed human activity tracking using smart sensor technology	Applied ML models to detect risk in human activities	DL models needed to be applied for accurate results
Pavleen *et al.*[25]	2019	Applied different ML techniques to predict patients health	Through ML several diseases prediction is done through ML models	Privacy and security for data needs to be applied
Richa *et al.*[26]	2021	For accurate results ML algorithms were applied to the public health dataset	Various data sources are utilized for collection of data	Proposed approach for the real-time environment needs to obtain
Priyan *et al.*[27]	2018	Wearable sensor data used to detect cardiac disease	Apache HBase is used to store large amount of data	Effective mobile ambulance method is to be determined
Kashif *et al.*[28]	2020	Predictive ML model for smart mobile health	Experimental results measure the accuracy and effectiveness of the model	Model use limited features for prediction
Hamza *et al.*[29]	2022	IoT- based smart healthcare is analyzed	IoT-based smart healthcare is examined, and several ML strategies used RF, NB, and K-mean algorithm	Deep Nural Network to be implemented for better results.
Muhammad *et al.*[30]	2021	Challenges faced by elderly people in healthcare	Benefits of the proposed model, the better quality of life for elderly people	Security and Privacy issues are not considered
Aashay *et al.*[31]	2018	WBASN and the GPS module are used to track and monitor soldiers	ML algorithm applied to collected data for analysis	Efficient and suitable cluster head algorithm could be implemented
Joseph *et al.*[32]	2021	Datas of heartbeat, body temperature, and glucose is collected from sensors and analyzed using ML techniques	ML algorithms used to diagnose diseases as data collected from wearable sensors	Security algorithms needed to be implemented for securing IoT based device
Aparna *et al.*[33]	2019	Challenges and solution of implementing fog computing for smart grid system in 5G Environment	Fog computing impact on energy management cost, response time, and transmission delay is analysed	Examining dynamic energy trading, as well as privacy and security considerations related to the smart grid
Ying *et al.*[34]	2022	Data Integration and causation analysis for wearable devices in the Context of 5G Technology	Addressing important and relevant topics in context of 5G and wearable devices	Investigating user feedback as well as developing scale methods for implementing and deploying real-world scenarios
The proposed approach	2023	ML-based activity classification and recommendation system to improve personalized healthcare	ML techniques used for classification of activity	-

Chapter 3

System Model and Problem Formulation

3.1 System Model and Problem Formulation

The system model and problem formulation of the proposed scheme are presented in this section.

3.1.1 System Model

The system model diagram for IoT-based smart wearables for personalized healthcare using 5 G-assisted machine learning (ML) is depicted in 3.1. The smart wearable devices, represent as W_i, such as smart wearable devices and Fitbit devices, are equipped with IoT-based sensors that collect data denoted as $D_i = x_1, x_2, ..., x_n$ from individuals. Each data point x_i corresponds to a specific health parameter measured by the wearable device. This data is transmitted via the 5G mobile network to a collection gateway, denoted as G, where it undergoes preprocessing and feature extraction operations denoted as $F_i = f_1, f_2, ..., f_m$. The preprocessed data F_i is then forwarded to a cloud server, denoted as S, which is designed to handle large-scale data storage and processing. The server stores the collected data in a database, denoted as DB, which can be represented as $DB = (F_1, y_1), (F_2, y_2), ..., (F_k, y_k)$, where F_i represents the feature vector corresponding to the ith individual, and y_i represents the corresponding health label or class assigned to that individual. The stored data in DB is utilized for data classification using various ML models. The ML models, such as Support Vector Machine (SVM), Decision Tree (DT),

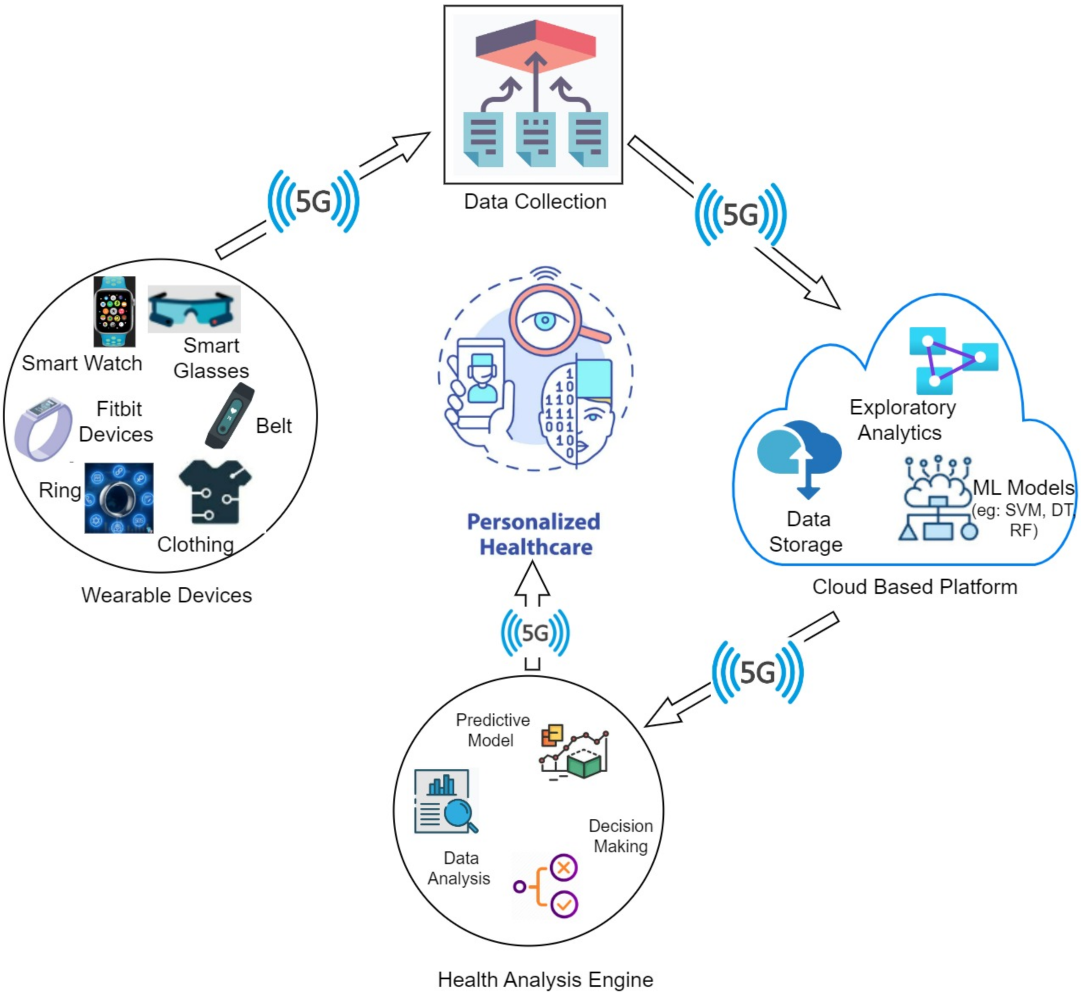

Figure 3.1: System Model Diagram

Random Forest (RF), and Naive Bayes (NB), have been used to analyze the data and make classifications based on learned patterns and features. The output of the ML models provides valuable insights into the individual's health status and can be represented as a predicted label or class y_i^1 for a given feature vector F_i. Based on the health analysis classification of activities like waking, running, sitting, and self-paced walking is identified by the machine learning model to recommend improved personalized healthcare for the person. The recommendations include suggestions like improving sleep quality, increasing physical activity, and maintaining a healthy diet. .

3.1.2 Problem Formulation

The smart wearable devices, represented as W_i, such as smartwatches and Fitbit devices, are equipped with IoT-based sensors that collect data denoted as $D_i = \{x_1, x_2, ..., x_n\}$ from individuals. Each data point x_i corresponds to a specific health parameter measured by the wearable device. This data is transmitted via the 5G mobile network to a collection gateway, denoted as G, where it undergoes preprocessing and feature extraction operations denoted as $F_i = \{f_1, f_2, ..., f_m\}$.

The preprocessed data F_i is then forwarded to a cloud server, denoted as S, which is designed to handle large-scale data storage and processing. The server stores the collected data in a database, denoted as DB, which can be represented as $DB = \{(F_1, y_1), (F_2, y_2), ..., (F_k, y_k)\}$, where F_i represents the feature vector corresponding to the ith individual, and y_i represents the corresponding health label or class assigned to that individual.

The stored data in DB is utilized for data classification using various ML models. The ML models, such as Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and Naive Bayes (NB), have been used to analyze the data and make classifications based on learned patterns and features.

The modified objective function can be defined as:

$$O = \max \{Pred_{activity}(i)\} + \min(L)$$

where $Pred_{activity}(i)$ represents the activity prediction using different ML models such as SVM, DT, RF, and L denotes the communication channel round trip latency.

Considering the classification task performed by the random forest, the objective function can be modified as:

$$O = \max\{Pred_{activity}(i)\} + \min(L) + \frac{1}{n}\sum_{i=1}^{n}(1 - y_i)$$

Here, n represents the total number of individuals or samples in the dataset. The last term $\frac{1}{n}\sum_{i=1}^{n}(1-y_i)$ captures the accuracy classification error by penalizing instances where the random forest misclassifies the individuals (i.e., $y_i = 0$ for individuals that should have been classified as $y_i = 1$).

By maximizing the security term, minimizing the latency term, and considering the accuracy classification error, the objective function provides a comprehensive measure for evaluating the performance of the random forest model in terms of accuracy, latency, and security.

Chapter 4

The proposed Approach

4.1 The Proposed Approach

This section demonstrates the proposed system architecture of an IoT-based smart wearable analysis for personalised healthcare using 5G-assisted machine learning. The proposed approach is divided into three layers. Layer 1 is Healthcare Data Sensing and Collection Layer. Layer 2 is Cloud-based Data Storage Layer. Further, layer 3 is the ML-based Healthcare Analytics Layer. Figure 4.1 shows the proposed system architecture for IoT-based smart wearable analysis for personalised healthcare using 5G-assisted machine learning.

4.1.1 Healthcare Data Sensing and Collection Layer

In the proposed system, the first layer is Healthcare Data Sensing and Collection Layer used for collecting end users' data from smart wearable IoT-based sensor devices. These IoT-based wearable devices are attached to the human body to collect the individual/user's health data in a continuous form. When the healthcare measure exceeds its normal value, then the wearable device sends an unusual activity alert message to your wearable devices. This alert message is collected and stored in the database continuously. The proposed system uses 4G and 5G mobile networks to transfer healthcare data and enable necessary action in an emergency. These latest technologies help in the betterment of an individual's health by giving an alert message on devices. The IoT-based wearable sensors collect the data from sensor nodes of wearable devices. These wearable devices are worn by an individual and collect the data of day-to-day activities from wearable device sensors and move toward the access point or other wearable devices. These wearable

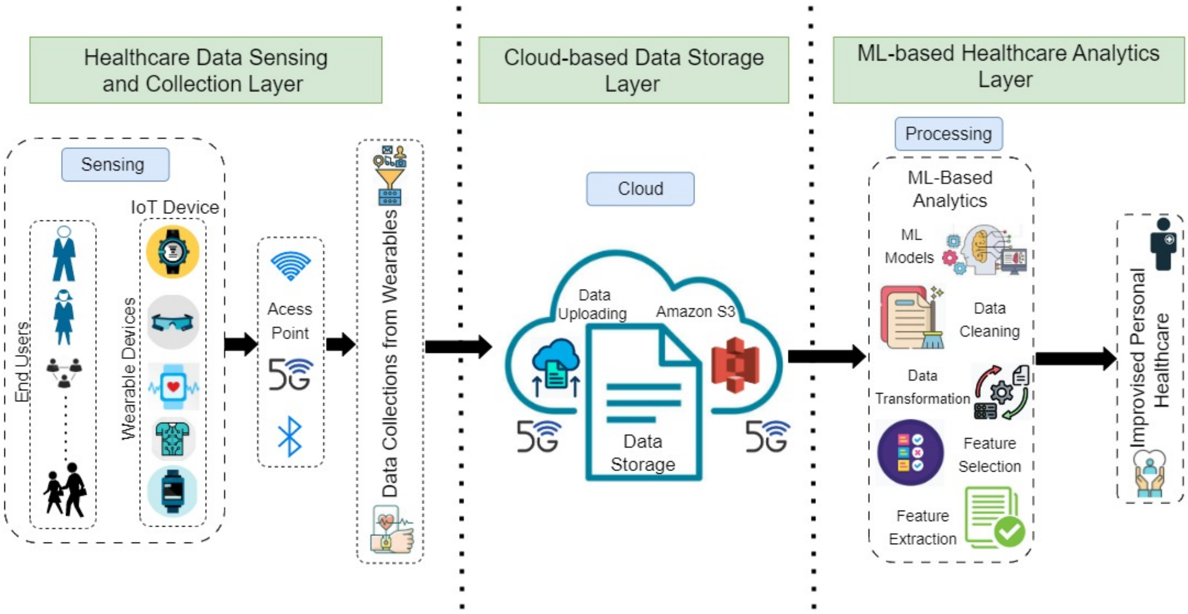

Figure 4.1: Proposed System Architecture

device sensors operate on lower frequencies in the range of 402 and 405 MHz for data transmission. The collected data is forwarded to the save on cloud storage. Amazon S3 cloud storage is used for data storage. [Smartphones are also connected to wearable devices for data collection, as the smartphone is connected to wearable devices and connected to sensor nodes and data can be collected directly] Sensors nodes can directly be connected to smartphones by which data can be collected directly through the access point.

4.1.2 Cloud-based Data Storage Layer

The IoT-based sensor devices attached to an individual would collect through a 5G mobile network data from wearable devices. A large volume of data is generated from smart wearable devices. It is challenging to store this large data using traditional data processing methods. So, the Amazon S3 cloud framework is used for supporting multiple machine learning models. The IoT-based healthcare monitoring system addresses the issue by using scalable and elastic cloud computing technologies. To obtain the virtual computer machine with database access, an Amazon account must be set up. The's3cmd tool' approach is initially used to upload the healthcare data gathered from smart wearable devices to the Amazon basic storage service S3. So, when an individual's healthcare data measurement is higher than it should be, IoT-based wearable devices report those healthcare measurements to Amazon S3. A distributed file system using a 5G mobile network, wifi, and Bluetooth is used to store a large amount of data.

As the IoT-based smart wearable device sensors would collect all the data of day-to-day activity, a large volume of data is produced, and storing this large amount of data using traditional processes is difficult. So, this proposed approach used Amazon S3 Cloud, a cloud architecture that supports a variety of machine learning models, which creates an environment to connect IoT-based smart wearable devices via the cloud and lacks scalability and security difficulties. The data collected from smart wearable devices would be transferred through a 5G mobile network and subjected to continuous analysis using machine learning models like random forest (RF), support vector machine (SVM), Naive Bayes (NB), and decision tree (DT). Supervised learning algorithm called random forest creates numerous decision trees and merges them to improve accuracy and stability.

4.1.3 ML-based Healthcare Analytics Layer

Data collected from smart wearable devices data collection and the utilization of 5G mobile networks for transmitting data to the cloud have emerged as a promising approach. This process involves forwarding the collected data from wearable devices through the high-speed and low-latency 5G network to the cloud, where it is securely stored. In this research, the collected data file is imported into a collaborative file with the necessary libraries, allowing for seamless data analysis. The dataset, formatted in the .CSV format, is loaded and ready for further analysis. To ensure data quality and reliability, the data is subjected to a comprehensive cleaning process. This involves checking for missing values using the .isnull() function and addressing any duplicate entries that may be present. Notably, the dataset used in this study exhibits no null values, enhancing the integrity of the data. The subsequent steps encompass data preprocessing and model building, with a focus on analyzing the mean value of the activity group. From the dataset, a total of 19 features are selected, enabling a comprehensive exploration of the data and subsequent model development. Overall, the process of collecting smart wearable device data, leveraging 5G connectivity for data transmission and implementing essential data cleaning and preprocessing steps to ensure reliable and accurate analysis.

Algorithm 1 Random Forest for Personalized Healthcare Analysis

procedure RANDOMFORESTHEALTHCARE(X, Y)
    Input: Sensor data matrix X of shape $m \times n$, corresponding target labels Y.
    Preprocessing: Perform feature scaling or normalization on X.
    Training: $RFModel \leftarrow$ BuildRandomForest(X, Y)
    Prediction: $Y_{\text{pred}} = \text{Predict}(RFModel, X_{\text{test}})$
    Evaluation: Compare predicted labels Y_{pred} with true labels Y_{test}.
    Output: Trained random forest model $RFModel$ and evaluation metrics.
end procedure=0

Chapter 5

Experimental Results

5.1 Performance Evaluation

This section highlights the performance evaluation and dataset description of the proposed scheme.

5.1.1 Dataset Description

The dataset used for this study is collected from the Apple watch series 8, which is worn by an individual over a period of one month. The watch is set up to collect continuous data on exercise, workouts, day-to-day activity, and physical activity. Data is collected using IoT-based sensors, which are designed to be non-invasive and comfortable to wear. The data is locally stored in the wearable device and synced with the individual's iPhone, where it is securely stored using Apple's Health application (framework). The dataset includes observation of one month, with a sampling rate of one observation per minute. The dataset consists of hourly data in 31*26 rows and columns.

5.1.2 Stimulation Setting

The proposed system architecture model has been implemented on the Windows 11 operating system (OS) configured as Intel(R) Xeon(R) CPU @ 2.20GHz, 12.7 GB RAM using Python as a functional programming language. The different open-source libraries including Pandas v1.0.4, Numpy v1.18.4, and Keras v2.3.1 perform diverse computations related to machine learning (ML) libraries. The SVM, RF, DT, and NB of ML models are applied for the classification of activity to improve personalized healthcare.

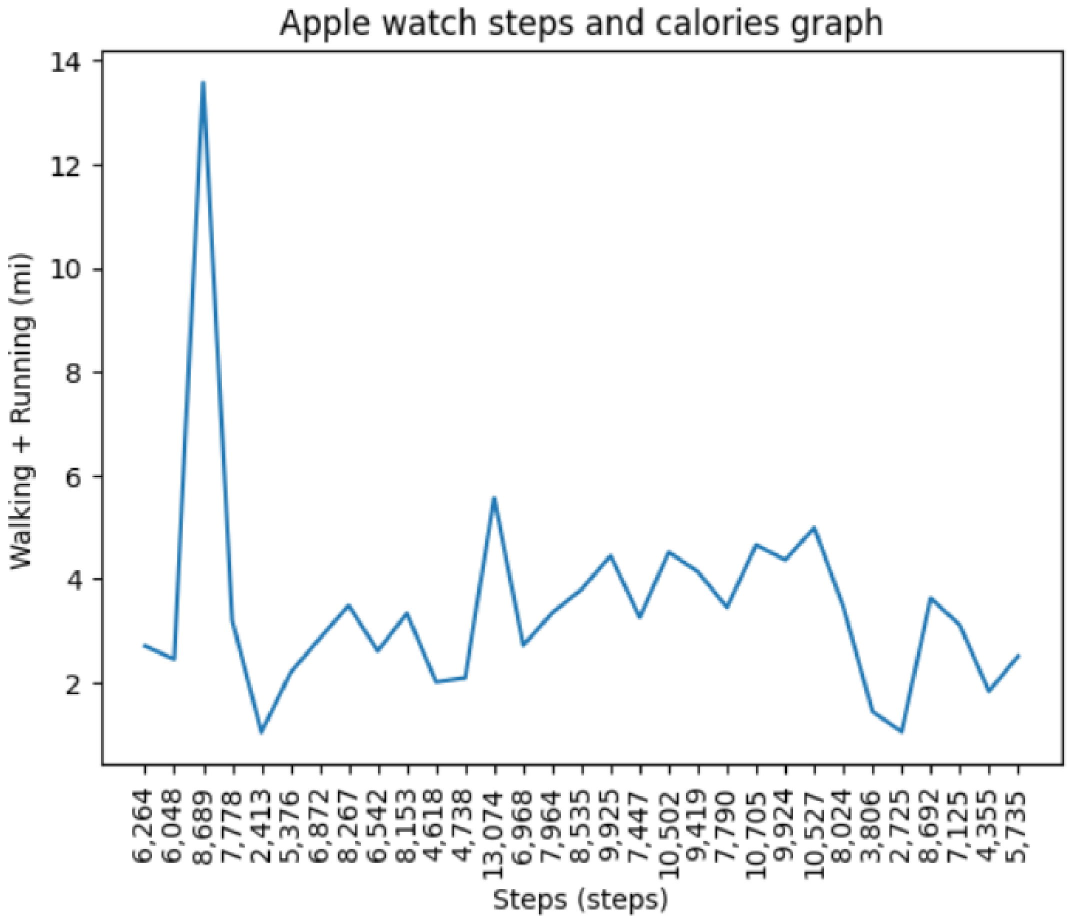

Figure 5.1: Apple watch steps and calories count graph

5.1.3 Experimental Results

In the beginning, all simulation parameters are set, Table

The graph depicts the comparison of the Apple watch's heart rate and distance covered through walking. The scattered plot graph predicts the heart rate and distance covered through walking. The plot predicts the walking distance, on average the density increases from 0.0 to 0.6 distance covered and increased heart rate from 60-120. Apple watch steps and calories count graph predicts the total steps count and walking plus running in miles is calculated. The last graph shows the age group of an individual and activities carried more from the age group 20 - 40. All the activities carried out are more from age 20-40 as compared to age 45-55.

Figure 5.1 predicts the data of walking plus running rate per day. The line graph predicts the walking steps for 31 days. Total 31 days steps count of individual data collected from a smart wearable device named Apple watch series 8. The x-axis shows the steps count per day for 31 days and the y-axis shows the walking plus running rate

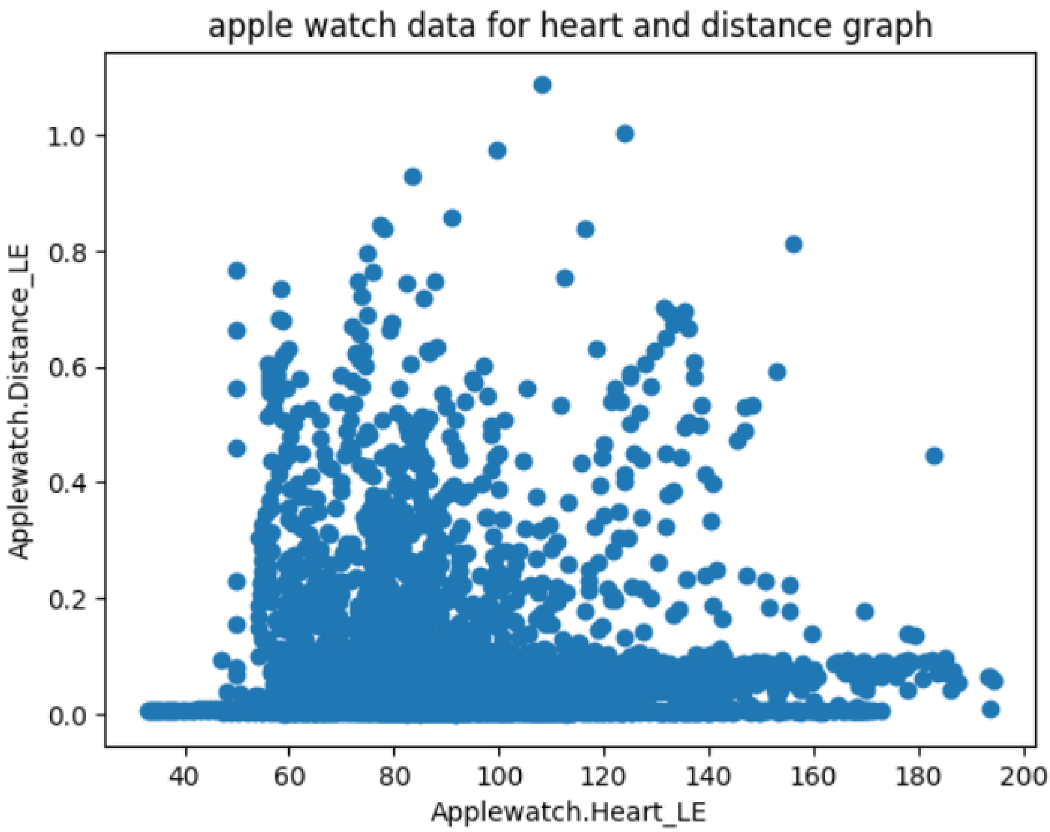

Figure 5.2: Apple watch data for heart and distance graph

Table 5.1: Comparision Table

	Acurecy	**RMSE**	**MSE**	**MAE**	**R2 Score**
Decision Tree Classifier	78.53152434	1.325060796	**1.755786113**	0.53471668	**0.409851283**
Random Forest Classifier	**89.14604948**	0.938661491	0.881085395	0.269752594	0.703852644
Support Vector Machine	45.57063049	**2.150558123**	4. 624900239	**1.402234637**	-0.55450537

per mile.

Figure 5.2 graph shows the data collected from wearable devices of an Apple watch distance and Apple watch heart rate. 0.0-1.0 data on the y-axis shows the data of Apple watch distance in miles. X-axis shows the heart rate of an individual from 40-200. The graph shows the density from 0.0-0.6 and the heart rate from 40-120 is denser as compared to others which shows that the activity is done more as compared to other data.

Figure 5.5 graph shows the activities of people from different age group and their activities. X-axis shows different activities of lying, sitting, self-paced walking, and running. Y-axis shows the different age groups ranging from 20 to 55. The graph shows the age 20-40 group activity is more healthy as compared to the age group from 45-55.

Figure 5.4 shows the latency comparison between 4G (LTE-A) and 5G networks with

Table 5.2: Comparision Table

	Acurecy	**RMSE**	**MSE**	**MAE**	**R2 Score**
Decision Tree Classifier	75.762	0.6483	0.4203	0.3016	0.8609
Random Forest Classifier	**84.237**	0.4888	0.2389	0.1847	0.9209
Support Vector Machine	76.101	0.6876	0.4728	0.3169	0.8435

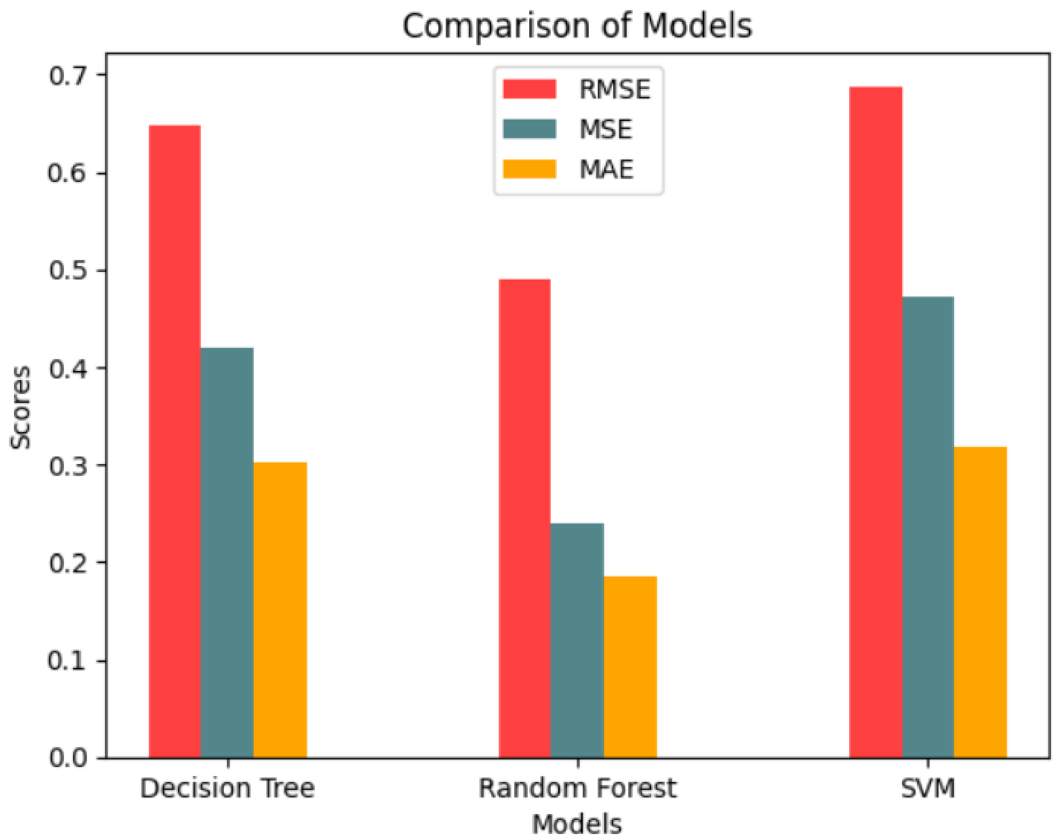

Figure 5.3: Comparision of results

the number of data transactions on the x-axis and latency in milliseconds (ms) on the y-axis. The graph showed a red line representing latency with LTE-A and a green line representing latency beyond 5G. The red line showed an increasing trend, indicating increasing latency and an increasing number of data transactions. As the green line, which predicts represents more than 5G technology, showed lower latency values compared to LTE-A, and the upward trend was less pronounced. This graph suggests that 5G technology offers better latency and enables faster and more efficient data transactions compared to 4G networks. The observation highlights the potential benefits of adopting advanced wireless technologies for future network deployments.

Table II is a comparative analysis of three classification models: Decision Tree (DT) Classifier, Random Forest (RF) Classifier, and Support Vector Machine (SVM). Perfor-

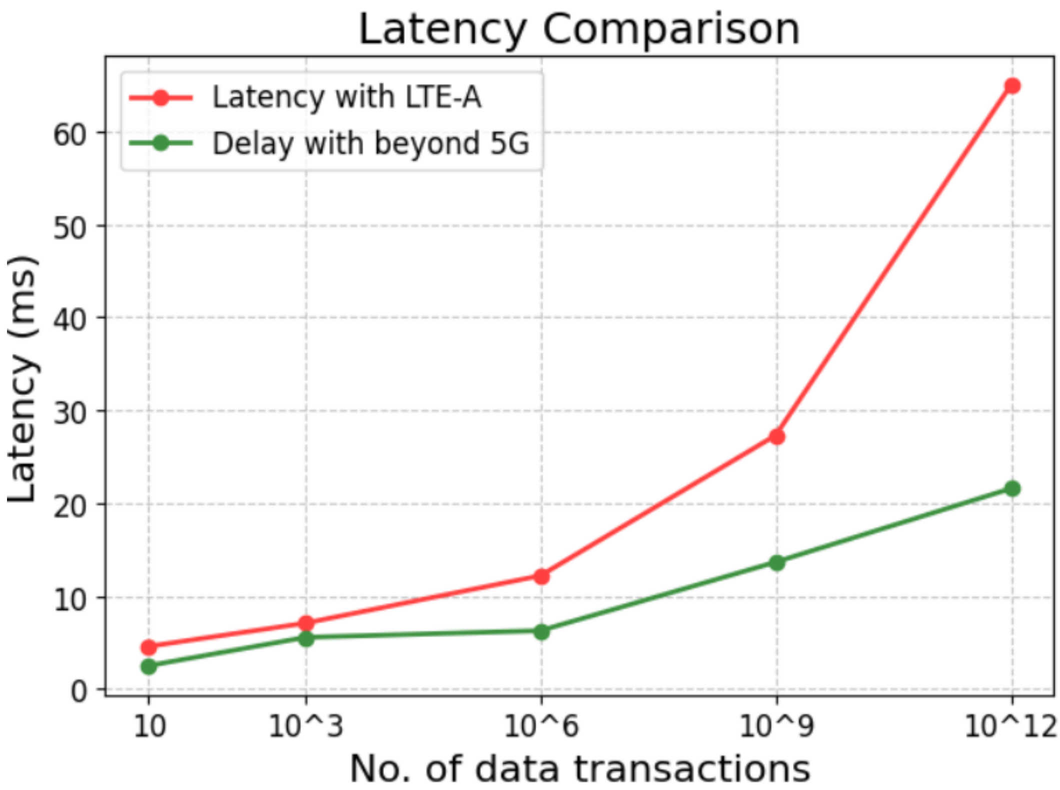

Figure 5.4: 4G and 5G Latency comparison

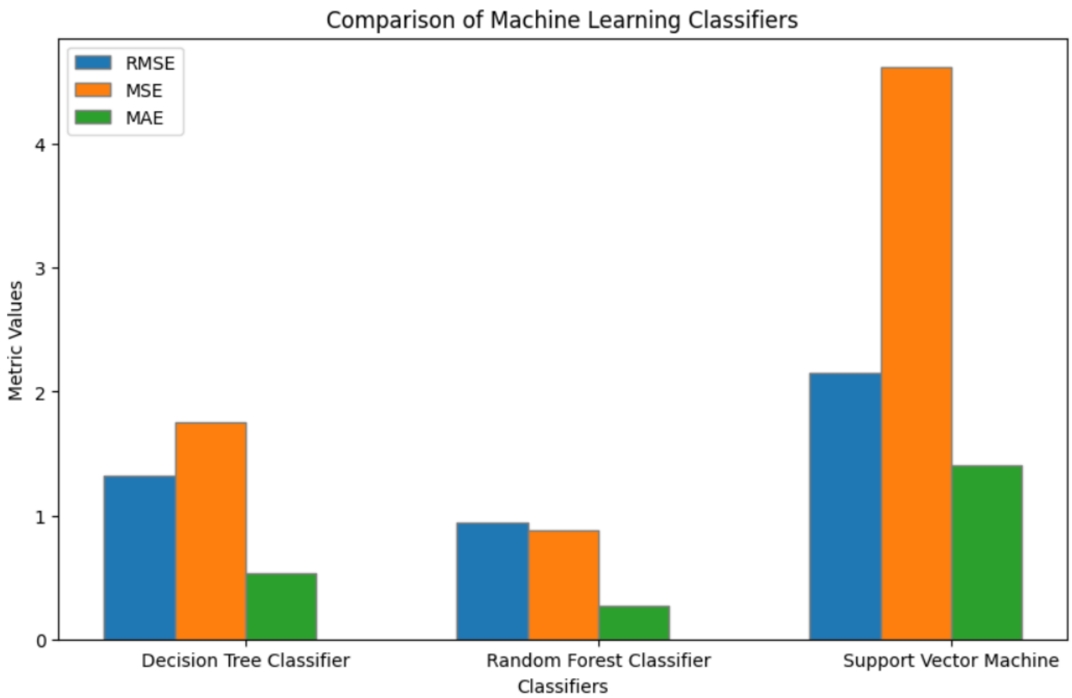

Figure 5.5: Graph of age and activity

mance using several evaluations of metrics, including Accuracy, RMSE, MSE, MAE, and R2 Score. Among the models, the Random Forest Classifier demonstrated the highest accuracy of 89.15%, the lowest RMSE of 0.94, MSE of 0.88, and MAE of 0.27, as well as the highest R2 Score of 0.70. These results indicate the Random Forest Classifier's superior predictive capability and ability to explain the variance in the data. The Decision Tree Classifier achieved an accuracy of 78.53%, RMSE of 1.33, MSE of 1.76, MAE of 0.53, and R2 Score of 0.41, suggesting moderate performance. In contrast, the Support Vector Machine exhibited significantly lower accuracy (45.57%), and higher errors (RMSE: 2.15, MSE: 4.62, MAE: 1.40). Based on these results, the Random Forest Classifier emerges as the most effective model for our classification task, demonstrating its potential for accurate predictions and suitability for similar research contexts.

Table III shows the comparison of the performance of three classification models: DT, Rf, and SVM. Their performance is evaluated using various metrics including Accuracy, RMSE, MSE, MAE, and R2 Score. The Random Forest Classifier exhibited the highest accuracy (84.237%), lowest RMSE (0.4888), MSE (0.2389), and MAE (0.1847) values, and the highest R2 Score (0.9209), indicating its superior performance compared to the other models. The decision Tree Classifier has achieved an accuracy of 75.762%, RMSE of 0.6483, MSE of 0.4203, MAE of 0.3016, and R2 Score of 0.8609, while the SVM achieved an accuracy of 76.101%, RMSE of 0.6876, MSE of 0.4728, MAE of 0.3169, and R2 Score of 0.8435. These findings highlight the effectiveness of the Random Forest Classifier in our classification task, suggesting its potential for accurate prediction and modeling in similar contexts.

Chapter 6

Conclusion

In this paper, we proposed an IoT-based smart wearable analysis for personalised healthcare using 5G-assisted machine learning. Smart wearable devices have increased their popularity in recent years. Activity Data is gathered from smart wearable devices and preprocessing is performed. In this work, the analysis and comparison of different machine learning models on healthcare data. The models considered are Decision tree (DT), Random Forest (RF), and Support Vector Machine (SVM). The evolution of the model has been done based on the accuracy, root mean square error (RMSE), mean squared error (MSE), mean absolute error (MAE), and r2 score. From the result, it is observed that random forest performed the best in terms of accuracy. In the future, the study can be further expanded to acquire data security and privacy for various healthcare data collected from IoT-based smart wearable devices.

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