DATA FUSION WITH MULTI-SENSOR DATA AND HEALTH MONITORING

Sidra Mahnoor
01-247182-016

A thesis submitted in fulfilment of the
requirements for the award of degree of
Masters of Science (Information Security)

Department of Computer Science

BAHRIA UNIVERSITY ISLAMABAD

OCTOBER 2020

Approval for Examination

Scholar's Name : ______________________________ Registration Number:

____________________ Enrollment: ____________________________

Program of Study: ____

Thesis Title: ____

____

It is to certify that the above scholar's thesis has been completed to my satisfaction and, to my belief, its standard is appropriate for submission for examination. I have also conducted plagiarism test of this thesis using HEC prescribed software and found similarity index ____%. that is within the permissible limit set by the HEC for the MS/M.Phil degree thesis. I have also found the thesis in a format recognized by the BU for the MS/M.Phil thesis.

Principal Supervisor Signature: ______________________________

Date: ________________

Name: ________________________________

Author's Declaration

I, Sidra Mahnoor hereby state that my MS thesis titled "DATA FUSION WITH MULTI-SENSOR DATA AND HEALTH MONITORING" is my own work and has not been submitted previously by me for taking any degree from this university or anywhere else in the country/world.

At any time if my statement is found to be incorrect even after my graduation, the University has the right to withdraw/cancel my MS degree.

Name of Scholar: Sidra Mahnoor

Date: 26-11-2020

Plagiarism Undertaking

I, solemnly declare that research work presented in the thesis titled

"Data Fusion with multi-sensor data and health monitoring"

is solely my research work with no significant contribution from any other person. Small contribution / help wherever taken has been duly acknowledged and that complete thesis has been written by me.

I understand the zero tolerance policy of the HEC and Bahria University towards plagiarism. Therefore I as an Author of the above titled thesis declare that no portion of my thesis has been plagiarized and any material used as reference is properly referred / cited.

I undertake that if I am found guilty of any formal plagiarism in the above titled thesis even after award of MS/M.Phil degree, the university reserves the right to withdraw / revoke my MS/M.Phil degree and that HEC and the University has the right to publish my name on the HEC / University website on which names of scholars are placed who submitted plagiarized thesis.

Scholar/Author's Sign: ______________________

Name of Scholar: Sidra Mahnoor

Dedication

To my beloved mother, father and family

Acknowledgements

In preparing this thesis, I was in contact with many people, researchers, academicians, and practitioners. They have contributed towards my understanding and thoughts. In particular, I wish to express my sincere appreciation to my main thesis supervisor, Professor DR. MUHAMMAD MUZAMMAL (Head of the department), for encouragement, guidance and critics. I am also very thankful to my Class fellows for their guidance, advises and motivation. Without their continued support and interest, this thesis would not have been the same as presented here. Their views and tips are useful indeed. Unfortunately, it is not possible to list all of them in this limited space. I am grateful to all my family members.

Abstract

In this era, wearable devices play an active part in the health care area and a different monitoring system. Wearable tracker research has been vigorously centered around by the scholarly community, including chronic diseases like heart rate and others. Researchers have utilized procedures in measurements, machine learning, and different fields to research, arrange and foresee daily personal activities. In this work, the dataset predicts and marks the chart medical treatment reactions, enforces desired bedtimes, tracks general fitness, predicts unwanted diseases, and provides current and future behavior advice to fulfill fitness goals. This study is focusing on finding abnormal behavior patterns within FitBit dataset to predict unusual diseases. For the methodology using the learning algorithms such as Long Short-Term Memory (LSTM), Deep Neural network (DNN), and Support Vector Memory (SVM)as a classification model in the study. Also, the Univariate method, Recursive feature elimination (RFE), and Random forest(RF) classifiers for feature selection. The proposed system shows the performance on an accuracy basis. Through Random forest, we obtained the best accuracy with 85% accuracy as compared to other methods.

TABLE OF CONTENTS

LIST OF TABLE

LIST OF FIGURE

Abbreviations

BSN	–	Body Sensor Network
CNN	–	Convolutional Neural Network
Ch2	–	Chi- square
DNN	–	Deep Neural Network
LSTM	–	Long-Short Term Memory
ML	–	Machine Learning
RF	–	Random Forest
RFE	–	Recursive feature elimination
RNN	–	Recurrent Neural Network
SVM	–	Support Vector Machine

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

Back in time when fitness trackers or smartwatches were not made and it was really hard to monitor everyday activities and health problems. Most people suffer from health problems and chronic diseases grow rapidly. After introducing the fitness tracker and smartwatches overcome the personal health problems people easily track their everyday activities and manage personal health. Fitness trackers or smartwatches are very user friendly and easy for the person to use. According to the World Health Organization report, non-communicable diseases (NCDs) such as heart diseases, cancer, diabetes, and other chronic diseases counted up to 71% of deaths worldwide[1].

Most of the people did not visit doctors for a checkup or not record their health conditions in their busy lives. After the development of wearable sensors and chips, it is very easy to control personal health problems or create alerts before happening something. In our modern era these fitness trackers such as Fitbit, MI bands, Jawbone, and other popular fitness trackers. These devices have the sense of monitoring the heart rate, sleep time in hours, minutes, how much distance you covered and steps, how much calories you burned.

Further, we observe that wearable gadgets are the new trend within the mobile device, which is supported by increasing demands. Individuals show an increasing interest in wearing a fitness band daily, which improves the quality of living in an exceedingly way that smartphones cannot accomplish[2],[3].In the different fields such as various technologies used by people Smartwatches, fitness tracker, smart glasses, and wrist bands for monitoring the daily routine[4].These gadgets are called wearable devices. Wearable Sensor watches are used to measure monitor and collect your daily activities[5] or, Observation about the physical situation[6], sports diagnostic[7].

During ongoing years, interests in wearable gadgets, have prompted the approach of the numerous gadgets inside the scope of surrounding, well being, brilliant city, shrewd home, industry, horticulture observing so on. the value recommendation of wearable, especially inside the wellbeing observing, has some cover with the exploration point remote body zone organization(WBAN)[8],[9].

These gathered information all the more regularly are shipped off a door (here PDA) and at times, subsequently to a worker to develop a modified information base. Notwithstanding, wearable gadgets and advances aren't a substitution wonder. There are numerous endeavors from ads and scholastic networks to style, create, and actualize such gadgets to work as performing various tasks apparatuses for a few purposes. These endeavors generally were made during the most recent ten years with a degree in wellness yet not restricted distinctly to this point.

1.1 Body Sensor Network

Body sensor networks in recent technology use in data processing techniques such as data fusion. The idea behind it is to predict the event in a human body before it happens. The prediction is collecting by different sensor data, which contains some collective values than the individual's raw data. The design is still no obvious as it required a continuous stream of data. The hardware of the sensors is economy and easy to use. BSN's provide alternative ways for analysis of people, e.g., recovery centers after a medical procedure[10], Through driving check emotion recognition[11], integration of Body sensor network data with the data of the environment[12]. Different machine learning techniques are used to check the accuracy, such as a random forest. It has recently shown that the random forest's accuracy can improve by incorporating the kernel method because it transformed it and provides superior prediction accuracy. BSNs give different use cases to monitor, analyze the problems, and predict the results. Use in different cases like detecting or preventing diseases through body activities, detecting emotions while driving, and other cases.

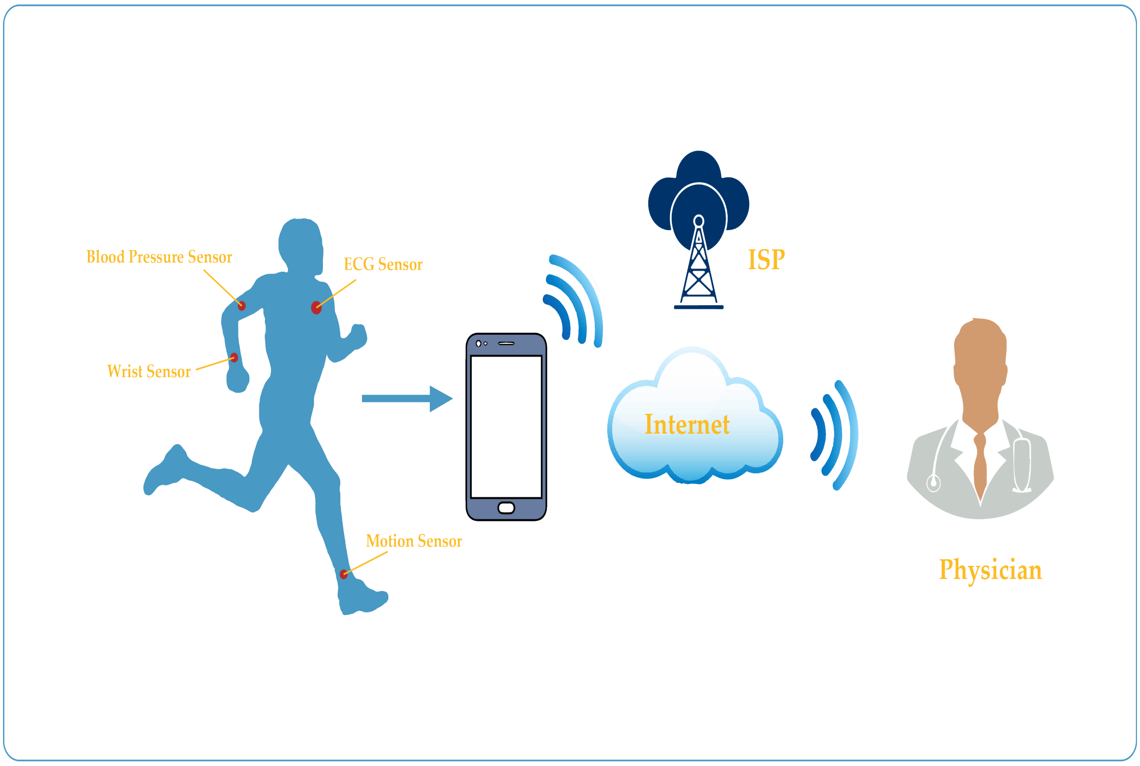

Figure 1.1: Overview of Body Sensor Networks

1.2 Data Fusion

Data fusion is a technique of inventing data from several mixed sensors, on different platforms, into a specific complex image. Also, the mix of records from over one sensor helps acquire reliable records than specific quantities acquired from a specific sensors data. There are three levels of fusion. Information on sensor fusion provides higher data at a basic level. At Feature level finds suitable options among numerous features coming back from different methods. The last level of fusion is the decision level, which mixed the selective data[13],[14],[15],[16],[17] &[18].Techniques of data fusion is association to the various information sources and availability of useful health care information play an vital role in the growing statically progressed experiences. Practically different body sensors and different sensors use wellbeing factors and shut elements. Those sensors' work expected to watch applications that convey the patient's information in the medical care network upheld the system. Information combination assumes a huge function in incorporating the information gathered by various gadgets to expand reliabilities, quality, and medical services frameworks' capacities. Information combination expects to part back vagueness, which is difficult to eliminate with one information stream[19].

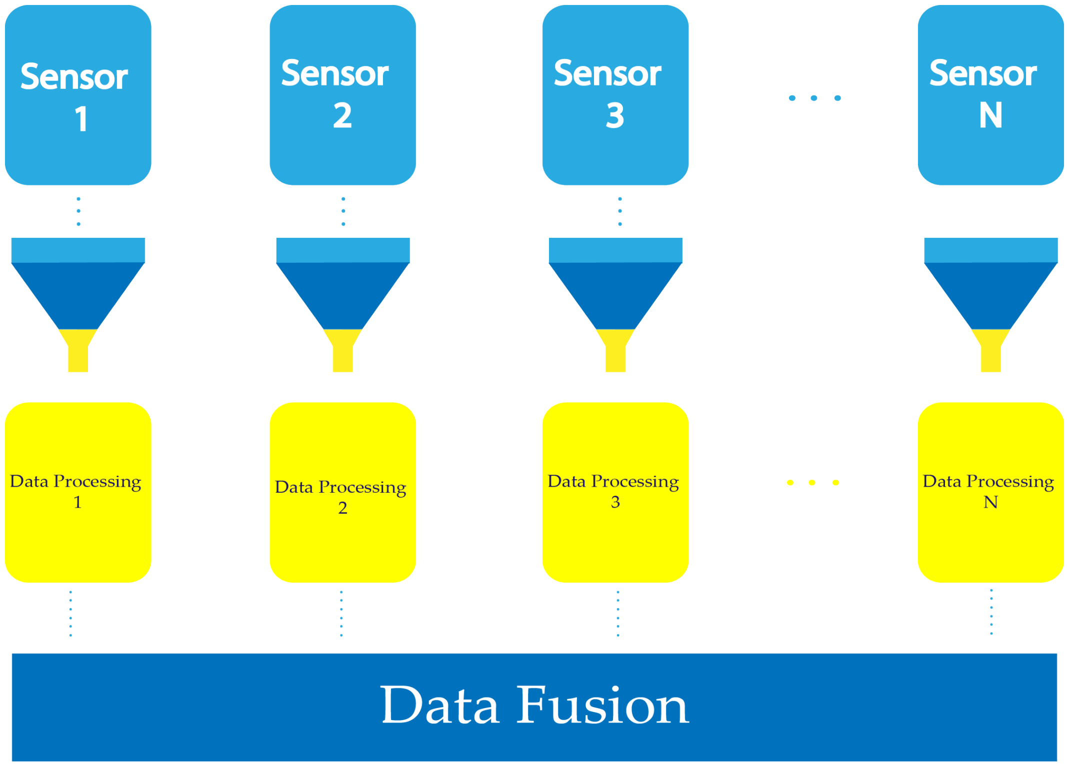

Figure 1.2: Data Fusion

1.2.1 Multi-Sensor Data Fusion

Multi-sensor information combination is a measurement preparing strategy to complete the dynamic and assessment, utilizing PC innovation to dissect and orchestrate mechanical partner with the insights of certain hubs under a positive model. It can develop multi-sensor realities artificially and mark the gadget as complete the important records to achieve an individual task. Incorporated and also merged multi-sensor records to complete as it ought to reflect natural qualities. It has the qualities of data repetition, correlative, continuous, and minimal effort; hence, it is utilized. Multi-sensor utilized combination data to anticipate. It is staggered preparing that utilizations to identify, relate, correspond, gauge, and incorporate the realities from a mix of sensors, acquires precise assessment and assessment of the check object state, and improve the observing framework's general presentation. Data combination is another technique for measurement handling, and it can upgrade sensor dependability at the cost of repetition and corresponding[20].

1.2.2 Multi-Sensor using Machine Learning

Machine learning is the study of algorithms and acts deprived of being programmed. Machine learning is used in various applications, including healthcare, for prediction, and better results through body activity recognition activities[21]. A deep learning approach to determining the standard of sleep used recurrent neural networks (RNN), convolutional neural networks (CNN), and long immediate memory RNNs (LSTM-RNN)[22]. Also, a clustering approach was taken on general activity tracker data to see daily patterns[23].

1.2.3 Multi-sensor using Internet of Things

Internet of things is the concept of linking devices to the web. IoT works through sensors that connect with devices over the web. IoT platform can pin the precise data that's useful and simply ignored. Also, it works in patterns to detect the issues before it occurs. a vital purpose is that whereas the foremost acquainted Devices connected to the web are computers just like laptops, servers, smartphones, tablets (for example, iPads), the development of IoT is far broader. specifically, everyday objects that haven't appeared as electronic within the least are beginning to come online with built-in sensors and microprocessors, communication with one another, and therefore the web. Other terms for the internet of things encompass Inter-connected devices, sensitive connected devices, wireless device networks, machines, and devices that communicate wireless, computing, intelligence, and practical matter. A method of describing the IoT, there are three main groups: observing and mastering the performance of homes and buildings, and health monitoring and enforcement systems[24].

The Internet of Things (IoT) introduces to the group of extraordinarily recognizable physical articles or gadgets and their virtual portrayals. While a portion of these IoT articles or gadgets have sensor-capacities to quantify/detect and impart their prompt ecological attributes (e.g., temperature, pressure, light), they, for the most part, can store and convey their exciting identifier. These articles or gadgets' capacity to detect and speak with the assistance of implanted innovation that takes into account cooperations with inner states and outside climate drastically impacts the included entertainers, area, and nature of choices made[25]

1.3 Problem Statement

- Most of the researcher's work had done on the Fit-bit dataset with the combination of other datasets.
- Still, the classification of the heart rate has not been the target.
- Nowadays Fitbit programmed devices play an important role in the health care area and most people use them for tracking their daily routine.
- This research is aimed at designing a reliable and operational system that classified the heart rate using a Fitbit sensor device.

Table 1.1: Comparison Between Health monitoring tracking systems

[26],[27]

Health Monitoring tracking systems	Specification	Problem
Fit bit	Track only sleep, walking steps, etc.	Not predict any diseases
Garmin Forerunner 735XT	Exercise tracker which record your ride, run, etc.using GPS	Not predict any diseases
Withings body Cardio Scale	Tracks your weight ,pulse rate,fat mass etc	Not predict any diseases
Wessoo K1 Fitness Tracker	Wesoo K1 tracks your workout,steps, calories burned, distance, sleep quality.	Not predict any diseases
Amazefit Equator Activity Tracker	Tracks your necessary health metrics including distance traveled, calories burned, steps taken, and sleep quality.	Not predict any diseases
Toobur Fitness Tracker	The device tracks your activity and sleep.	Not predict any diseases
GARMIN VIVOFIT 3	The device tracks your sleep, run, etc	Not predict any diseases
Fitbit Ionic	It tracks sleep duration and consistency	Not predict any diseases
ZUCOOR Smart Bracelet	Fitness Tracker Pulse Monitor Blood Pressure Clock	Not predict any diseases
Teamyo Up	It tracks sleep, pedometer, distance, etc	Not predict any diseases

1.4 Research Objectives

- To perfume ML computation on sensors make these more effective data.
- To perform information handling and information collection, trailed by the investigation of the accumulated information of sensors
- To predict diseases better
- Increasing computation efficiency
- Reducing Cost
- Achieved a high level of quality
- To propose a validated wellness health score algorithm suitable for a medical environment

1.5 Research Questions

1. How much Fitbit dataset gives accuracy?
2. Which feature range is better for prediction?
3. How can the dataset clean and processes?

1.6 Our Contribution

Our contribution is as follow:

- We proposed a human body activity network system for heart disease prediction.
- We proposed a system using multi-sensor fusion data for the prediction.
- We use different machine learning methods with different selection methods for the best results.

1.7 Significance of the study

- The scope of this research is to help people in health care area through programmable wearable sensors which easy to use and accurate.
- Achieve a high level of quality.
- If we achieve computation efficiency which is very helpful in the area of the health sector.
- Focus on Cost reduction.

- It helps people to reduce health risks and motivate them to manage their health.

The primary goal of the research is to find the best feature which is useful in the data analysis of classification. For the implementation of random forest, the Recursive elimination feature and filter method have been used and also describe the comparison of the different machine learning algorithms, such as Deep Neural Network (DNN), Support Vector Machine (SVM), and Long – short term memory (LSTM). Further, we also use a different selection method to get the best accuracy.

1.8 Organization of thesis

The thesis organized as follows. Chapter 2:presents the related work about the body sensor network and its applications. Chapter 3 presents the Methodology details, data-set, and data processing. Chapter 4: presents the results, and chapter 5: presents the conclusion and future work.

CHAPTER 2

RELATED WORK

Wearable activity-tracking devices are a subset of personal assistant systems, regularly track the everyday routine associated with health and fitness. They use an accelerometer to regularly calculate user activities like daily activities, such as heart rate, the total number of steps, the total amount of calories burned, and sleep. An essential feature of wearable fitness smartwatches is programmed to collect data and communicate between the device and the webserver. Wearable devices involve the sensor to get the information through the body activities. BSNs have qualities like transmission capabilities, computation power, storage, and predication of early disease problems. Many forms of research were dedicated to developing health systems consisting of wearable devices.[28],[29], which recognizes the desires to own wearable sensors and conquering basic bottlenecks for wearable sensors and accordingly the clinical worthiness and interoperability in well-being information[29],[30], inventive wearable structures help convoluted medical care bundles and license ease wearable, non-obtrusive alternatives for constant check-in 24 hours as following in Bio-informatics, imaging processing, logical informatics, and community wellness. Nonetheless, inside the ongoing assessment of sensor data, while considering portable wellness observing structures, certainty examination.[28].Similar works performed[31],[32] wherein the creators likewise give valuable planning between exact sicknesses and which fundamental sign boundaries could likewise be estimated are material for the infection. Such ailments and ailments incorporate cardiovascular infections, breath diseases, renal maladies, stance and development control, recovery, Parkinson's sickness, pressure, neurological issues, Alzheimer's ailment, and dementia[28]. More sensor information (aside from the referred to vital indications) are considered inside the writing and EEG and casing temperature[29]. In any case, coordinating and deciphering sensor alarms while contemplating an influenced individual's realm keeps on being challenging[32].

There is various researcher's work on the fitness trackers, such as investigation on the essential factors of fitness tracker[33], in contrast, smartwatch and smart glasses worn by individuals[34],tracking your physical motions e.g. every step and heart rate through Fitbit or other Run keeper devices[35]. The fitness tracker is the type of wearable sensor which allows basic fitness modules such as counting steps, distance cover, and so on. It implies that individuals can utilize wearables for unexpected purposes in comparison to wellness following itself. Subsequently, although wearables are a significant idea in examining health problems following conduct, care ought to be taken in summing up the discoveries on wearable innovation to the space of wellness following invention. Eminently, the creators utilize the term ’movement tracker’ or ’fitness GPS beacon’ in this thesis rather than the generally used term called ’Fitness tracker’ as not everything exercises can be considered as physical action (for example, eating, stepping, or resting).

2.1 Body Sensor Network

BSN is the structure of devices that cover the human body for the benefit of the user.BNS consists of several miniaturized circuits combine to make a network. It is a low-cost implantable and wearable sensor used for tracking the health status or condition of a person. There is much application that used body sensor networks. body sensors are getting exceptionally famous in different applications like medical services, sports, insightful dynamics, amusement, military, and crisis circumstances. These sensors give precise and dependable data about the circumstance or movement happening whenever. This high responsiveness of these sensors has made carry on simple and safe. The effect of wearable sensors innovation has changed our lives in such a manner as it was finished by the versatile correspondence time a couple of a long time back. It has been seen that wearable sensors like frenzy alert catches are utilized for disturbing about conceivable medical issues as expected and its utility in the clinical field has been finished with incredible achievement. The significant worry of utilizing alarm caution catches is that it ought to be helpful and advantageous to wear unequaled by the user[36] There are different kinds of activities like body activity, heartbeat rates, internal heat level, beat action, muscle development, and different genuine data which can be observed by these body sensors[37],[38]. It has gotten simple to decide the weight of blood utilizing body sensors with a tweaked strategy for estimating blood vessel beat motions. This strategy has taken out the use of inflatable weight fold over the arms and results can be gotten by utilizing earphones and versatile contraptions[39][40]. Different exercises of a competitor’s dissected and estimated in the field of sports. Like an advance check, sweat examination, pulse estimation, and so forth, prior these estimations were done physically or in the research centers however, now these are conceivable by utilizing body sensors[41]. The wearable sensors ought to be extremely light in weight for the patients so the estimation of different exercises should be possible with no impediment. As the number of inhabitants in elderly individuals is expanding in the nation, costs of their clinical treatment are likewise expanding. It has been seen that as opposed to going through cash in emergency clinics utilization of body sensors can make the fundamental medicines for the patient at home. Sicknesses, for example, cardiovascular failures (torment in the chest), rest apnoea, and Parkinson infection can be checked to utilize body sensors[42],[43].

At the point when the patients are in recovery/therapy methodology and they need to follow a firm timetable, all the physiological exercises can be checked with the assistance of body sensors. Body sensors use procedures like augmented simulation pictures, acoustic criticism, and other restoring offices. Each sensor takes a shot at the state of a specific patient. The total action can be checked indirectly by wellbeing focus groups and guardians[44]. A keen detecting framework is additionally used to distinguish the fall of people at home, generally, fall is considered for elder and old individuals[45][46].

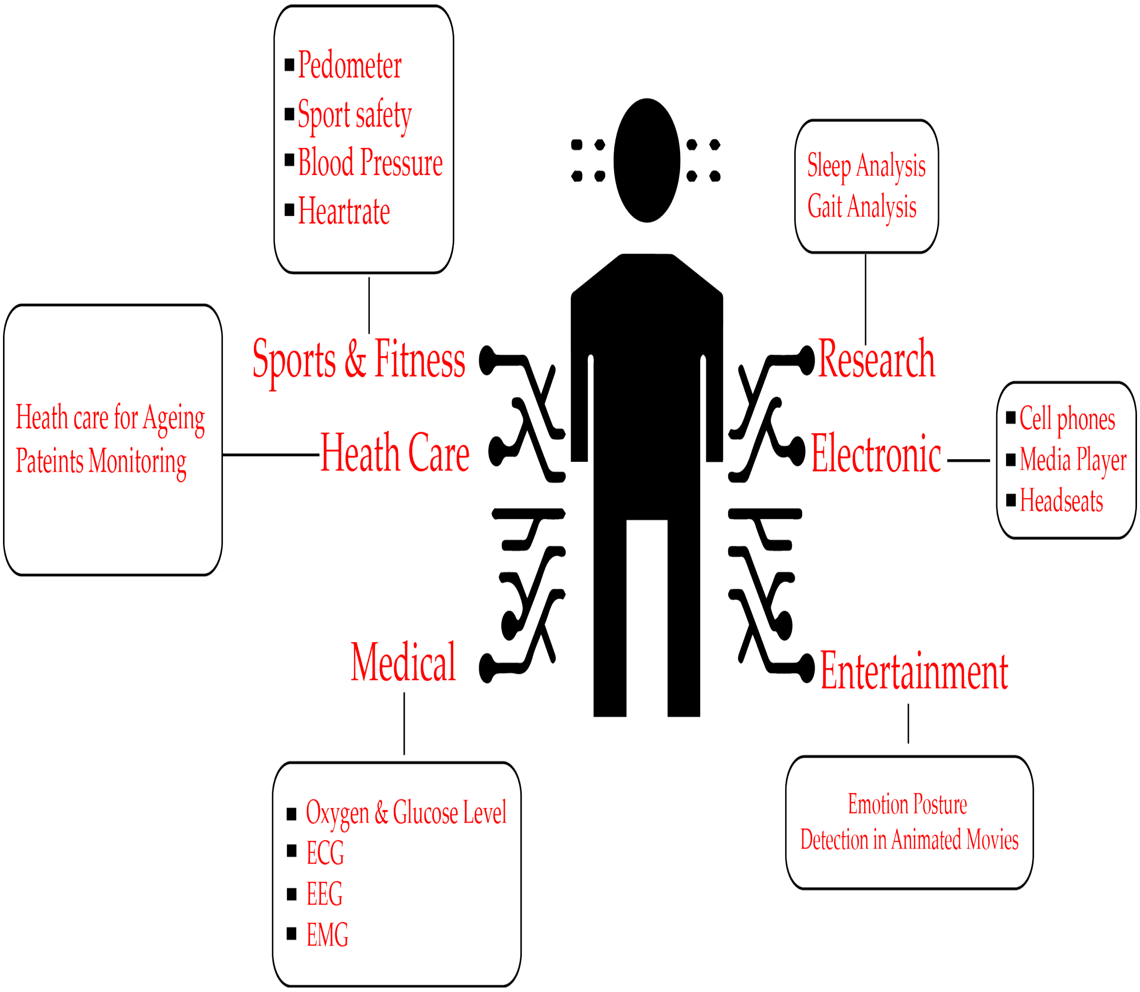

Figure 2.1: Body Sensor Network Applications

Table 2.1: Different research articles

Reference	Study	Dataset	Sensors
[47]	Timmermans et al. 2010	55 (Rehabilitation)	Physical activity.
[48]	Rednic et al. 2012	17(physical activity recognition Observational)	Physical activity
[31]	Atallah et al. 2012	105(Gait and fall)	Physical activity
[49]	Huang et al. 2014	104	ECG (Cardiovascular diseases)
[50]	Xu et al. 2014	14 (Physical activity recognition)	Physical Activity
[51]	Alshurafa et al. 2014	101 (Diabetes and nutrition)	Physical activity
[52]	Giuberti et al. 2015	24(Neurological diseases Observational)	Physical activity
[53]	Gong et al. 2015,	24 (Neurological diseases)	Physical activity
[54]	Xu et al. 2016	4 (Physical activity recognition)	Physical activity
[55]	Gong et al. 2016	42(Neurological diseases)	Physical activity
[56]	Nakamura et al.2017	25(Stress and sleep)	Physical activity
[57]	Naranjo-Hernández et al. 2018	10 (Asthma/COPD)	Vital signs
[58]	Kuusik et al. 2018	51(Neurological diseases)	Physical activity
[59]	Sok et al. 2018	13(Neurological diseases)	Physical activity
[60]	Haghayegh et al.2019	3085	Physical activity

2.2 Lifestyle predication

Lifestyle predication means general health monitoring. We monitor daily activities like walking steps, running, sleeping, and others through our daily activities and consumption habits, easy to predict lifestyle-related diseases such as heart-related disease, smoking habits, tumors, and more on the cause of deaths worldwide. Through a balanced lifestyle, we prevent lifestyle-related diseases[61].

2.3 Centralized and decentralized Data fusion

In the centralized data collected on the central node and process, and in the decentralized, all the sensors collect their information and transfer to the central node for data analysis.

2.4 Body Activity recognition

Now a day's condition of health care organization needs equipment's and methods to predict the physical health accurately. Body recognition means scanning body parts through sensors, including sleeping, running, walking, and others.

2.5 Pattern/Emotion recognition

In real-world data, many techniques and algorithms for pattern/emotion recognition used. There are few methods to recognition through numbers contained in vectors, images, text, face, audio detection, and physiological manner[10],[62].

2.6 Disease prediction

Nowadays, there is a severe disease that causes sudden death like heart, brain, and others. With the development of machine learning, it is possible to predict and even cure before it is too late that diseases become incurable before going to the disease in an incurable manner.ML gives the decision making power in healthcare[63],[64].Healthcare organizations are already using some techniques for predicting better results like electrocardiograms using for detecting heart disease similarly, ML-based ECG for recording the heart rate pattern, and many more.

2.7 Decision Making for Diagnosis

In the diagnosis hierarchy, decision-making is the main task for a health monitoring system to get information about the patient record and metadata[65].Decision Making extracts the information through sensors, which use to diagnosis the diseases[66]. The diagnosis/decision making is used for the abnormal detection pattern in machine learning abstract the useful information from device data such as events,alarms and other,for using as decision making for diagnosis [8]. Nevertheless, the diagnosis systems' difference is always using anomalous patterns for vital symptoms to make decisions. For more, the situation's problem, especially about patient's situations, wishes tremendous sturdy and worldwide records instead of a sensor's unique styles by itself[65].

2.8 FitBit

FitBit and other individual trackers turned out to be progressively well known as of late as individuals turned out to be more inspired by self-observing their wellbeing. They need to turn into a favored zone of study among information researchers, analysts, doctors, physiologists, and therapists, to call some scholastic examination regions. Distinguishing connections in complex time-arrangement information, as FitBit individual tracker information, can set up a way of life designs and identify deviations from these examples. With the powerful FitBit API giving advances and rest information constantly, hour, and now and then moment, exceptions are frequently simple to spot. Significantly more noteworthy is spotting conduct, which can anticipate when an exceptional occasion may happen. Exceptionally compelling to flow research is that the ability to anticipate future, or even not so distant future, conduct, upheld a client's Fitbit history. As plot inside the segment beneath, this may appear as only building up to standard commonplace use, or is utilized to tell when sick clinical patients are improving or weakening, or can even be taken to the level of endeavoring to send mechanized inspiration instructing messages to assist clients with evading earlier traps in their tracker-related objectives. These examinations target ascertaining a gauge conduct profile that future exercises are anticipated from or gaining practical experience in distinguishing atypical exercises during this setup target.

A non-thorough rundown of such wellness tracker gadgets incorporates Basis B1 Band, Bowflex Boost, Fitbit Force, Fitbit Flex, Fitbit One, Fitbit Zip, Fitbug Orb, Garmin VivoFit, MIO Alpha BLE, Jawbone UP, Misfit Shine, Motorola MotoActv, Nike+ FuelBand SE, The Polar Loop, and Withings Pulse. While the details and functionalities shift among these gadgets, they are altogether wearable and they all measure and track some type of 'wellness' boundaries (e.g., calories consumed, pulse, number of steps taken, rest beat). What recognizes these new ages of wearable wellness tracker gadgets from comparative gadgets of the past (e.g., pedometers) is their capacity to furnish consistent coordination with online interpersonal organizations. It could be said, at that point, these gadgets are important for the overall set that include the Internet of Things (IoT).

Several studies have occurred within the growing area of private health and fitness trackers. These studies range from necessary examinations of the accuracy[67],[68] and efficacy of the trackers[69]. Within the studies gazing change detection, some have looked into analyzing and visualizing statistic data[70], taking a statistical unsupervised learning approach to create dynamic models of human action[71], and breaking statistic data into sliding windows to calculate the importance of changes across each window to calculate importance[72]. A more machine learning and data processing direction is in love with many of the studies reviewed. One study looks into making predictions of use on a personal per-user basis (as critical comparing users to the complete corpus)[73]. Another further investigates using actionable, data-driven predictive machine get automated real-time coaching tips supported a user's current and historical Fitbit activity, the foremost successful model using the Random Forest algorithm[74].On the opposite hand, steps are considered to be a random effect, because the participant has some say in what percentage steps they need to attain.

Table 2.2: Research Paper on Fitbit and other Wearable Fitness tracker

Study	Paper Title	Approaches
T. Choksatchawathi et al.,(2020) [75]	Improving heart rate through Post calibration approach	HRR
A. Almogbil et al,2020 [76]	Fitbit GPS-tracker activities in forensic	GPS-tracked activities.
A. MacDermott et al 2019 [77]	Forensic analysis of Fitbit ,Garmin and HETP Wearable devices	GoldenCheetah & FitSDK
Z. Liang et al,2019 [78]	Sleep and walk detection with the combination of machine learning and re-sampling	Decision tree and random forest
Dijkhuis et al.,(2018) [74]	Personalized Physical Activity Coaching: A Machine Learning Approach	Random Forest
Z. Liang and T. Nishimura, 2017[79]	Comparison between EEG devices an d sleeping tracker of clinical devices	Off-the-shelf sleep tracking devices
Gary M. Weiss et al.,2016 [80]	Actitracker	Random Forest
M. Rahman et al.,(2016)[81]	Fitness tracker for secure management of low power	Sens.io.
Sathyanarayana et al., 2016 [82]	deep learning approach to determining quality of sleep	CNN,RNN & LSTM-RNN
C. M. Lee and C. W. Jung,2015 [83]	Radiation-Pattern-Re-configurable Antenna Using Mono-pole-Loop for Fitbit Flex Wristband	Monopole antenna
T. Tan et al.,2014 [84]	Using RFID and FitBit wristband monitoring the indoor activities	Active RFID

2.9 Fitbit types

Fitbit has categories in three types, such as Fitness tracker, smartwatches, and wearable wrist bands.

2.9.1 Fitness trackers

Fitbit fitness tracker is the popular devices for fitness purpose and play vital role in health problems. We can easily track our daily activities through which we can reduce our health problems. There are few fitness trackers of Fitbit as follow:

- **Fitbit Inspire 2**

Fitbit Inspire 2 is very popular and used for monitoring the optical heart rate.

Figure 2.2: Fitbit Inspire 2

- **Fitbit Charge 4**

Fitbit charge 4 is also used as a fitness tracker. It is used for monitoring heart rate, GPS location , swimming activities, NFs, and Altimeter.

Figure 2.3: Fitbit Charge 4

- **Fitbit Inspire HR**

It tracks the heart rate zone during the workout, and it also monitors the steps, the distance covered, the amount of calories burned, and so on.

Figure 2.4: Fitbit imspire HR

2.9.2 Smartwatches

After Fitbit fitness trackers we also discuss a few Fitbit smartwatches. Smartwatches are also very popular nowadays. There are few Fitbit smartwatches as follow:

- **Fitbit Sense**

Fitbit sense is the recent launch watch with advanced features. Fitbit sense is loaded full of new features such as ECG ,stress tracking, temperature checker, and other features like steps, calories, sleep time, hours, duration, everything.

Figure 2.5: Fitbit Sense

- **Fitbit Versa 2**

It is also used for monitoring the daily activities the whole day. It has a google assistance feature, body temperature monitor, and others.

Figure 2.6: Fitbit Versa 2

2.9.3 Fitbit wristband

- **Fitbit Alta**

Fitbit is the advanced form of Fitbit charge. It has a built-in heart rate and other tracker features.

Figure 2.7: Fitbit Alta

- **Flex Band**

Flex band is the known band. It is swim-proof, track laps of swimming, and automatic exercise recognition.

Figure 2.8: Flex band

- **Ace fitness Band**

The ace fitness band is introduced for the kids; it tracks the physical activities of the kids. It is a tiny wristband for kids.

Figure 2.9: Ace Band

2.10 Summary

This section analyses the related work in which various people already work on it and used different Fitbit wristbands with different features in different fields.Also mention the different type of Machine learning used in past research.

CHAPTER 3

METHODOLOGY

The past sections precised the research's introduction and related works, after giving a summary and explanation of body sensor and health monitoring to diagnose diseases. In this segment, we will explain the methodology of the system. The proposed method is the Human Body Sensor Activity Network (HBSAN). It will collect the fused data of different sensors, recognize the daily lifestyle routine, and predict the unexpected diseases.In this section, we use Scikit-learn with NumPy, pandas, and Matplotlib libraries, etc.For the hardware, I will use up-to three sensors for data collection in the proposed system. Therefore, this keeps up autonomy among detecting and result show. The potential equipment structure of the sensors is a wellbeing checking watch which is fit for estimating a variety of physiological measures. Further, as the sensor gadgets are remote, satisfactory battery life must be guaranteed to ensure consistent and dependable checking without interference. Besides, at least two devices will be required in the proposed framework.Fitbit smartwatch is chosen for collecting data for fusion because Fitbit is easily compatible with android and iOS phones and also we do not need any extra software for developing Application and deployment.

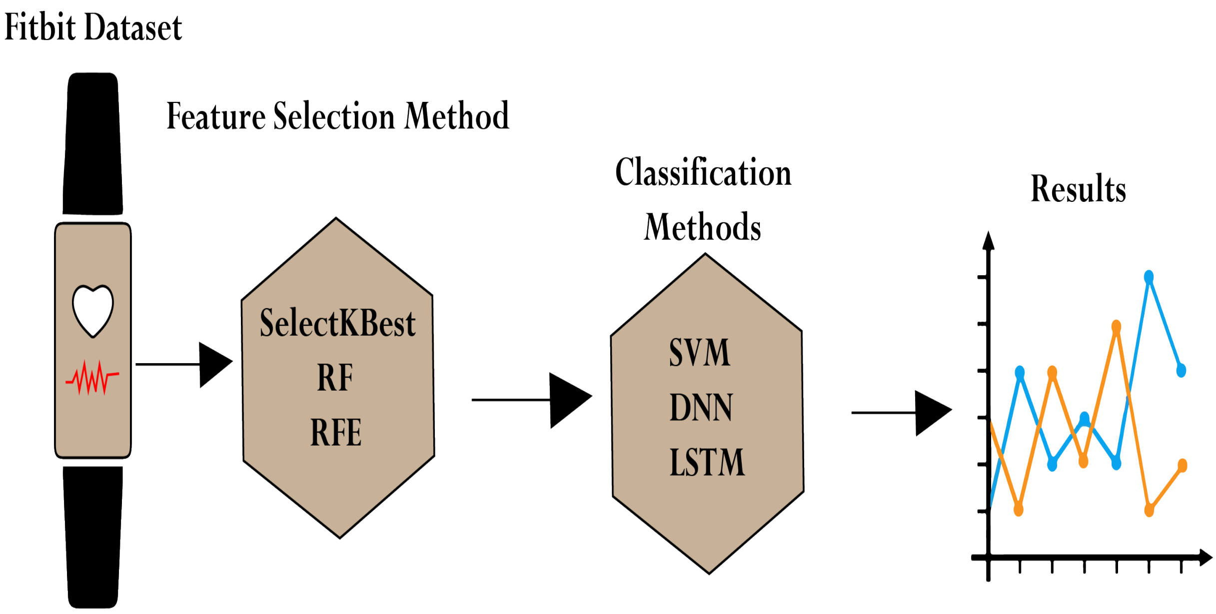

Figure 3.1: Work Flowchart

3.1 Approach

Learning algorithms in the health monitoring system plays an essential role in data analysis where sensors' extract useful evidence from a lower phase and connect them to the higher phase data illustration. In the proposed system of health, monitoring gives more attention to achieving the best classification accuracy. The main idea for the proposed system is shown in figure (3.2).

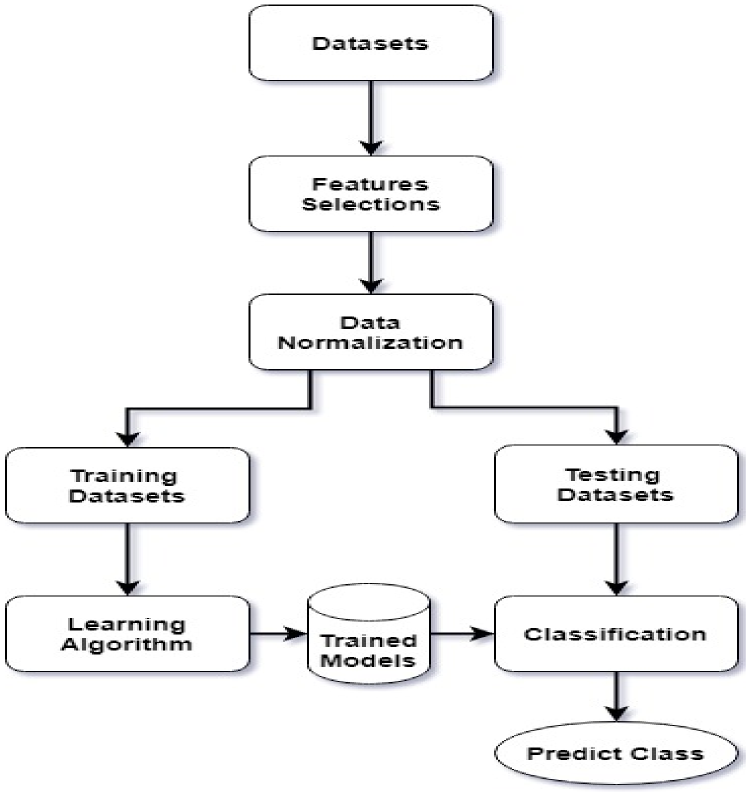

Figure 3.2: The Overview of the proposed system

In this figure, the data of sensors first enter the feature selection phase, then in the data normalization phase, where data labeling and data scaling performed, after that dataset is allocated into the training and testing phase to learn the model features and give real-world problems. After splitting the dataset, the Training dataset applied the learning algorithm and trained the model than in testing dataset applied classification for prediction and decision making of the input.

Algorithm 1 An outline of proposed system Algorithm

Input: Import Dataset (Fitbitdataset.csv)

Output: Display the results

Process

1. Using read_csv () function of pandas library for data loading.
2. SelectkBest feature = [score function, k = number of best feature]
3. Scaling the dataset
4. Split the dataset into train and test[train, test] = [70% , 30%]
5. Initialize the learning Algorithm
6. Model start initialized
7. Learning Algorithm initialize hyper parameter weights
8. Heart rate for training all epochs
9. Generate input
10. Forward pass
11. Backward pass
12. Update all weights

3.1.1 Dataset

We gather the activity data with the Fitbit watch sensor's help. The Fitbit watch gathered 15 features data from all the sensors: heart pulse, numbers of total steps consumed in a day, amount calories burned,the distance was covered, sleeping hours, heart rate, and others. The predication task will perform on the bases of recorded activities.

3.1.2 Feature Selection

Feature selection is the technique that chooses the best features automatically from the dataset. In feature selection process is utilized to achieve the subsection of the best-related features of the dataset deprived of reusing them. It is used for improving the information to achieve the best accuracy. Feature selection use in different fields, such as data mining and ML applications. The benefits of making feature selection are removing over-fitting, improving accuracy, and reducing training time [85]. The feature Selection method increases the significant data from present features and accomplishes the most noteworthy correctness of classifiers[86]. Feature selection is used in medical fields for the best problem-solving systems. Many types of research show that a ton of research has been accomplished feature selection worth referencing approaches. We performed different feature techniques to check suitable accuracy in various states in the classification algorithm. Here are the few methods used in the research (figure 3.2).

Filter Method

In the filter method depends on the information's overall uniqueness to be assessed and pick highlight subset, excluding any mining calculation. Filter techniques utilize the specific review rule, which incorporates separation, data, reliance, and consistency. Filter techniques use the vital standards of positioning procedure and utilization's the rank requesting technique for variable determination. The purpose behind utilizing the positioning strategy is straightforwardness, produce significant and pertinent highlights. The classification method will sift through unessential highlights before the characterization measure begins. The data prepossessing step filter method is used for feature selection, independent of any learning algorithm. It gives statistical scores that determine the correlation in the output variable.

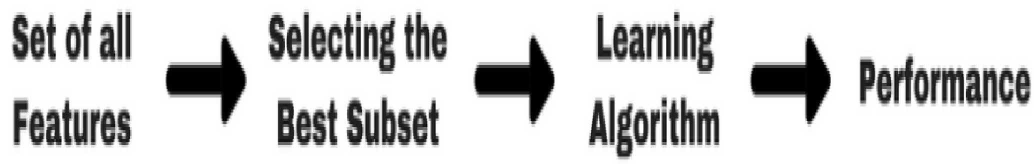

Figure 3.4: Filter feature selection method

One of the best approach of filter feature selection method is the univariate method is used to identify the important feature of the dataset. Each feature is selected according to specified criteria and on the base of higher scores and ranks. In univariate feature selection method select the best k features through SelectKBest () class. It use the F_classif distribution function(chi2())to obtained the p-values between 0 and 1[87].

3.1.3 Wrapper Method

In the wrapper method is used for improving mining performance and searches for the best feature algorithm for machine learning. Some typical examples of wrapper method feature selection include recursive feature elimination, forward feature selection, and backward feature elimination.

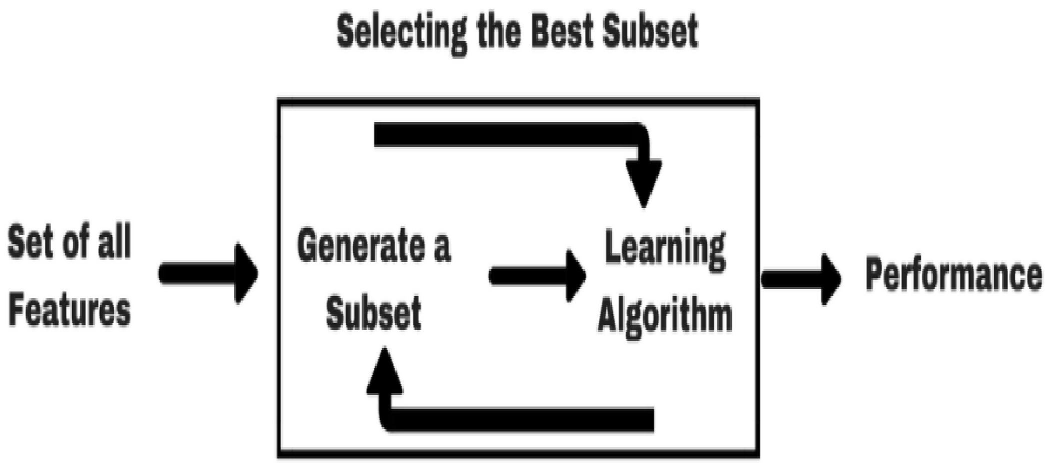

Figure 3.5: Wrapper method for feature selection

3.1.4 Recursive Feature Elimination(RFE)

Recursive feature elimination is the finest method of feature selection. It remove the weakest features in the datasets until the specify features are found shown in (Figure 3.6). RFE use three parameters to sklearn.

- First one estimator use fit method for machine learning models,
- Second one is n_features_to_select which select the number of features for process.
- Third one is steps which check the feature drops every time when RFE reduces the features.

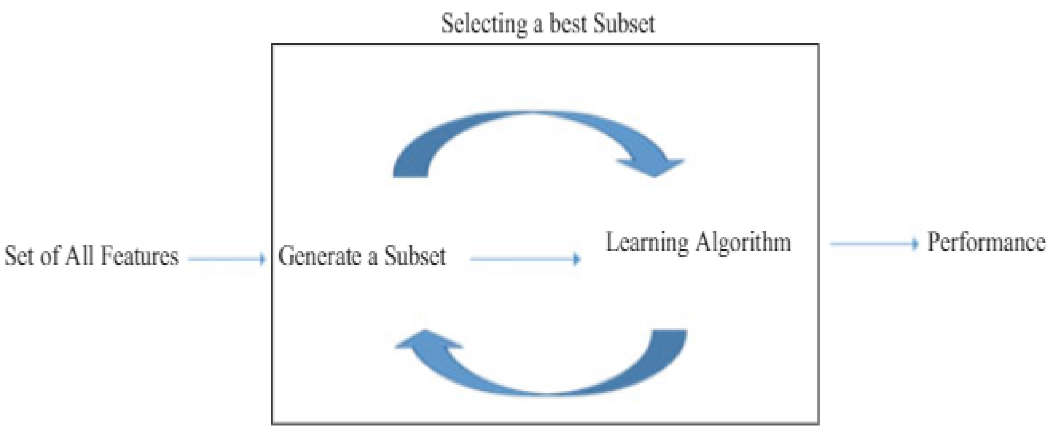

Figure 3.6: Recursive Feature Elimination

3.1.5 Random Forest

Nowadays, a random forest is a popular classifier in different fields. A random forest is a mixture of trees that create a forest with several trees in it. In the random forest, the highest numeral of the tree means higher accuracy in results. It works step by step and takes decisions. Its use to identify the diseases as well. The selection of the dataset randomization of the nodes while the construction of decision trees.

Algorithm 2 An ouline of Random Forest Algorithm

Input: Import Dataset (Fitbitdataset.csv)

Output: Display the results

Process

1. Using read_csv () function of pandas library for data loading.
2. Select RandomForestClassifier = Test features k = number of total features from m features]
3. Split the daughter node and using best split function
4. Calculate the votes for the target result
5. Consider the high votes as the final predication for target result.

3.1.6 Embedded Method

The embedded method is the iteration method that checks each iteration of the training model and extracts those features that contribute the most in the training model. The most usable and standard embedded form is the Regularization methods, which correct a component given a coefficient limit.

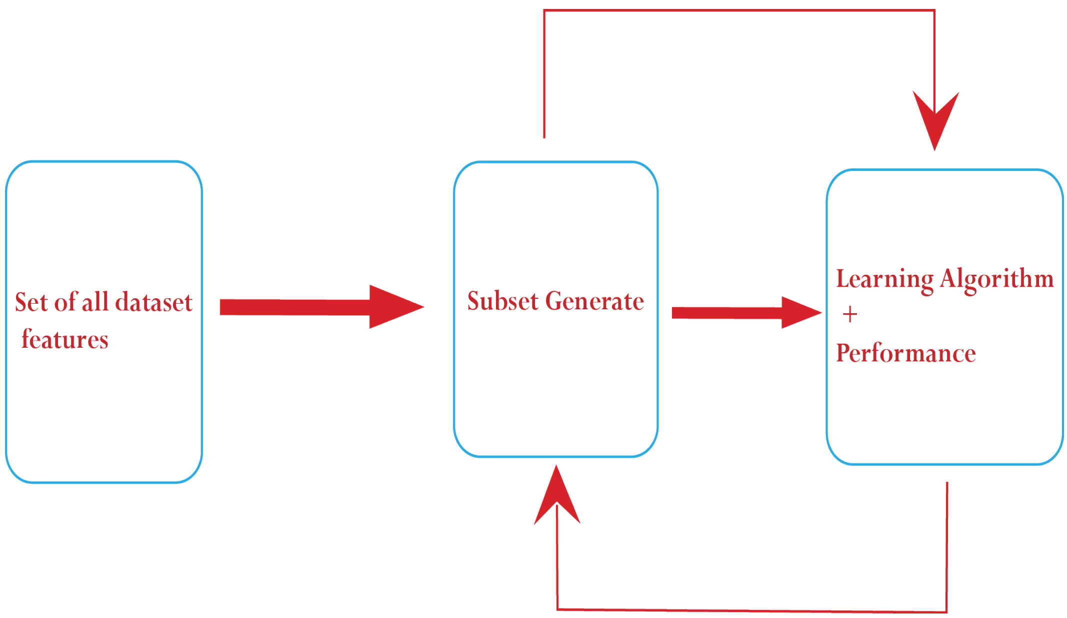

Figure 3.7: Embedded Method

3.1.7 Data normalization

Data normalization is the method of scaling the data set. It means to re-scale the variable between 0 and 1 or -1 and +1.Normalization use when the big difference occurs in different data features.Data normalization is used to reduce and eliminate the redundancy in data. Through data normalization, it easy to do sorting, searching, and creating indexes faster in less time shown in the figure .

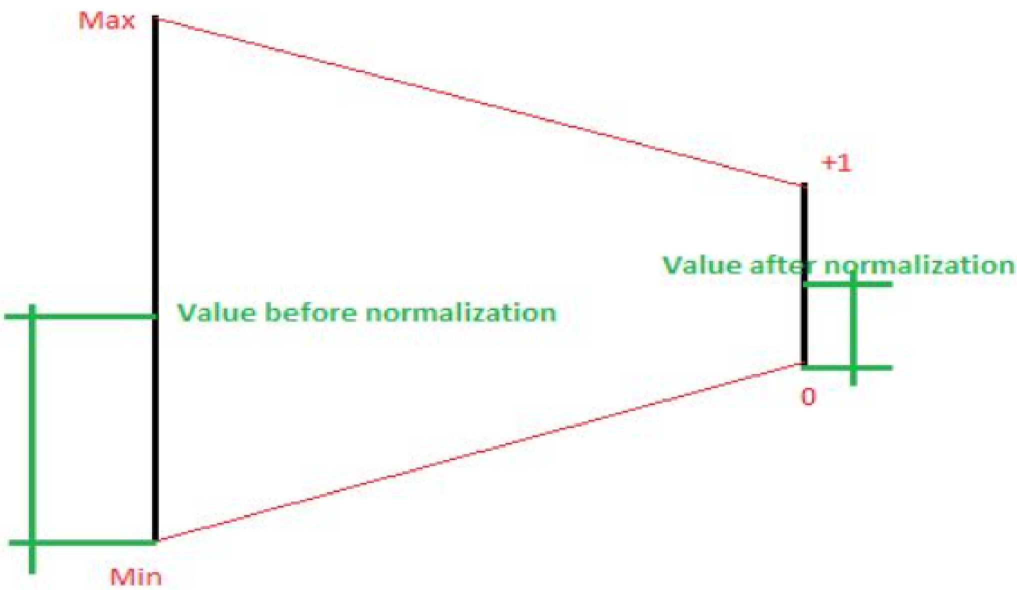

Figure 3.8: Data Normalization

There are different type of data normalization techniques.

- Zscore
- MinMax
- Logistic
- LogNormal
- TanH

3.1.8 Zscore

This technique converts all the values a in Zscore.In each separate column mean and standard deviation compute.

$$z = \frac{x - mean(x)}{Stdev(x)} \tag{3.1}$$

3.1.9 Min-Max Scaling

This scaling method used to re-scale the data in the range [0,1].

$$X[:, i] = \frac{(x[:, i] - min(x :, i)}{(max(x[:, i]) - min(x[:, i])} \tag{3.2}$$

3.1.10 Logistic

Logistic use for transformed the values in the column through following formula.

$$z = \frac{1}{1 + exp(-x)} \tag{3.3}$$

3.1.11 Log Normal

Its coverts all the values to a lognormal scale.

$$z = lognormal.CDF(x; ; \mu, \sigma) \tag{3.4}$$

3.1.12 Tanh

It converts all the values in hyperbolic tangents.

$$p(k/x; \theta) = \frac{[E(Y/x)^k e^{-E}(Y/x)]}{K!} \tag{3.5}$$

So we used Min-Max data normalization for normalize the dataset.
For normalization using Box-Cox Transformation

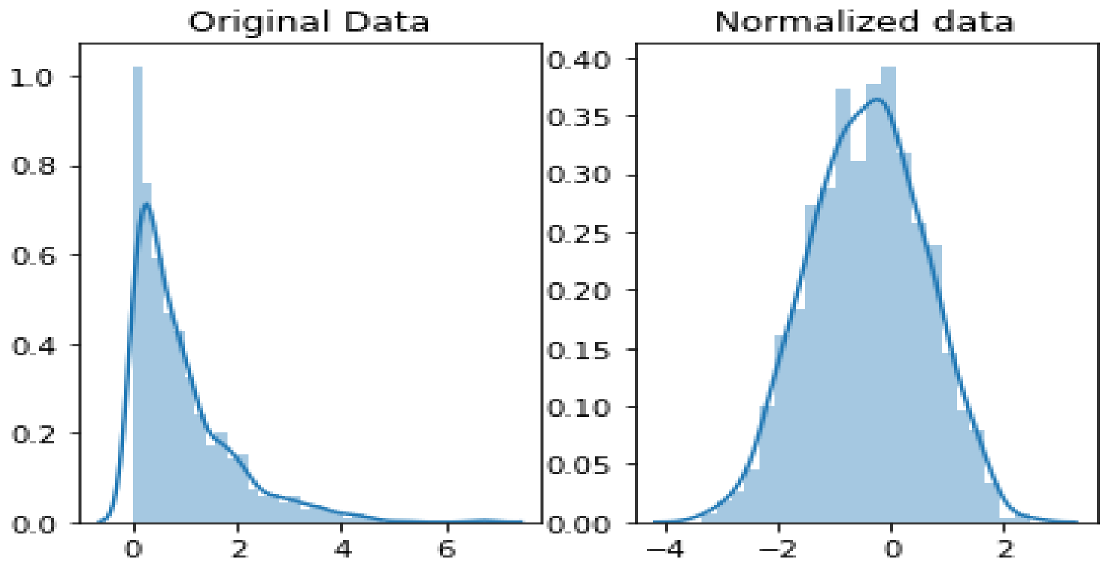

Figure 3.9: Normalize data

3.1.13 Learning Algorithm

Machine Learning is applied to show machines how to deal with the information all the more productively. In the survey's wake, we cannot read the example or concentrate data from the report. We apply a machine learning algorithm. There are a few learning algorithms that we use in the research.

3.1.14 Deep Neural Network

The machine learning model Deep Neural Network is the sub-type of an artificial network that uses multiple layers as input and output layers. In linear or non-linear relationships, DNN checks the mathematical operation for changing the input into the output.

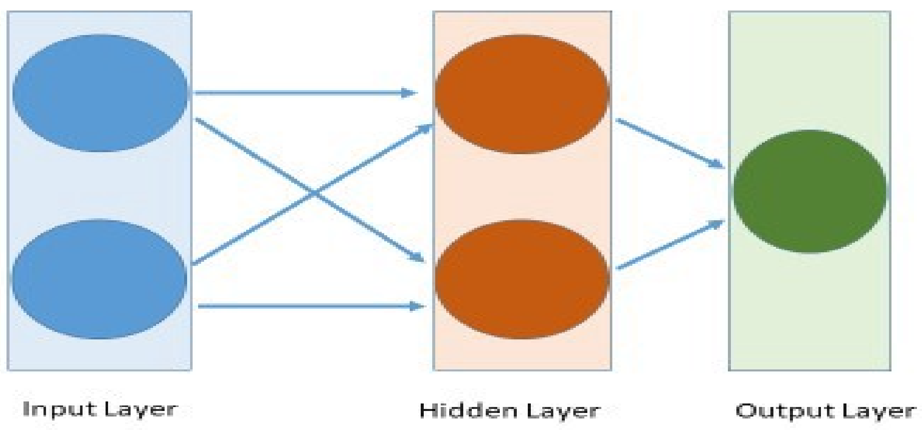

Figure 3.10: Deep Neural Network

3.1.15 Recurrent neural networks RNN

RNN works on node connections; it saves the particular layer's output and feeds as input for predicting the layer's outcome. Different layers of nodes of the neural network press together in the form of a single layer of RNN. There are three parameters of networks A, B, and C.

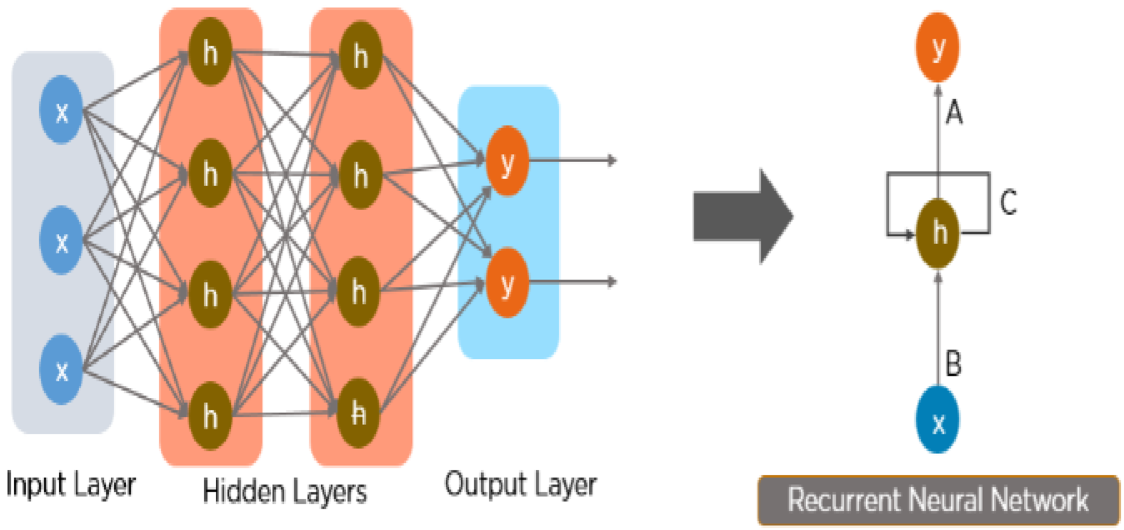

Figure 3.11: RNN model

3.1.16 Long Short-Term Memory (LSTM)

The machine learning model long Short-Term Memory is the subtype of Recurrent neural networks that stores the information in memory for an extended period and uses a general-purpose feedback connection. Its uses for sequences, pattern recognition, and image processing application.LSTM consists of three central units, which include input, output, and forget gates.LSTM decides when the information enters to neuron and calculate the previous time step. It also agreed on the based on current input by itself.The figure represents the LSTM model.

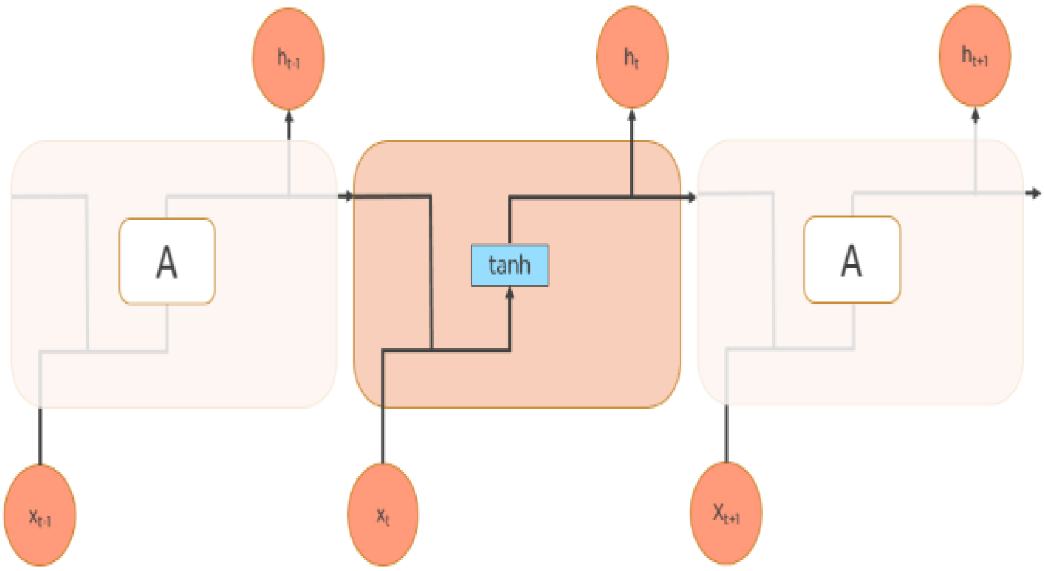

Figure 3.12: Long-Short Term Memory

3.1.17 Support Vector Machine

A support vector machine (SVM) is one of the most used machine learning models. Prepared to order concealed data by inferring chosen includes and building a high dimensional hyperplane to isolate the information from two classes to frame a phone model. Since the SVM can deal with high dimensional information utilizing a negligible preparing set of highlights, it is late stylish for physiological information in clinical applications.

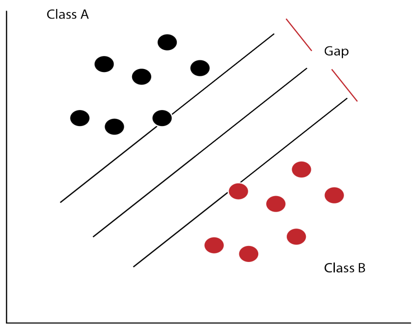

Figure 3.13: Support Vector Machine

3.2 Accuracy Method

For calculating the accuracy predication errors we going to use this accuracy equation.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.6}$$

3.2.1 Threshold values

Table 3.1: Heart rate rhythm type

Normal	60 to 100 bpm
Tachycardia	HR $>$ 100 bpm
Bachycardia	HR $\leq 60bpm$

3.3 Summary

This chapter's main impact: it gives the details of the proposed system methodology how data is collected for the fused data of different sensors, recognizes the daily lifestyle routine, predicts the unexpected diseases, and gives warning to the end-user and informs the respective hospital or doctor. Therefore, the structure of the framework must meet a variety of necessities to fulfill these objectives. So, sensors collected the heart rate data and then fused the data to make the prediction or diagnosis of the diseases. This study's primary effort is to analyze the range of different features used to find out the best characteristics from the classification dataset analysis. We also use different selection methods for the critical metric. With the help of the Fitbit dataset, we proposed our system in which we used a different machine learning model such as Deep neural network(DNN), Long – Short term memory (LSTM)Support Vector Machine (SVM), and to find useful information for health monitoring. The machine learning model works with different feature selection methods such as Random Forest (RF), Recursive feature elimination (RFE), and univariate feature selection (SelectKBest with F) to find the best accuracy.

CHAPTER 4

ANALYSIS & RESULTS

This section presents the facts of different experiments with the results that we performed. We present feature selection results with various classifiers, then data processing, and a trained model for the results. We divided the dataset into 70% of the trained dataset and 30% in the testing dataset, examining the performance variation.

4.1 Results and Experiments

The Fitbit dataset consists of 600 instances and 15 attribute variables. The results obtained by the pre-trained models and the classifiers (SVM, DNN, and LSTM) are listed in table 4.1. In the univariate method, recursive feature elimination, and Random forest classifier method; initially, 15 variables are used as input and given to the model, which is used as a machine learning algorithm. The output carried out the most important subclass of variable features given by as inputs. Firstly, all the features are trained by learning algorithms, and every feature is separately kept. After that, the minimum amount of factors of features are going to be removed. As an output of RFE, SelectkBest using f_classif and RF of every repetition of the trained process. The dataset selected the best features and provided inputs to SVM, DNN, and LSTM for the classification process.

4.2 Feature Selection Results

For feature selection, we used three classifiers such as the univariate method, RFE, and RF. In the analysis, RF gives the best result on the Fitbit dataset. RF techniques are very valuable and effective in choosing the best features. We don't need to utilize all features of the dataset. Therefore, it will impact the preparation time. As compared to other methods, RF gives better results which we obtained based on our proposed system.

Table 4.1: Feature Selection Result

Feature Selection	SVM	DNN	LSTM
SelectKBest	70.44	77.64	79.54
RFE	72.99	80.75	81.63
Random Forest	75.25	82.04	85.05

4.3 Accuracy Analysis

Our system performances depend on the accuracy which we obtained through the analysis. We used the three classification models with different feature ranges.

4.3.1 Features Analysis

We used 600 instances of the Fitbit dataset with 15 features in the study used the random forest with DNN, SVM, and LSTM.

4.3.2 Random Forest Result

Analysis of important features of classification models using random forest. It gives the different accuracy result on the different range of features shown in figure(4.1).

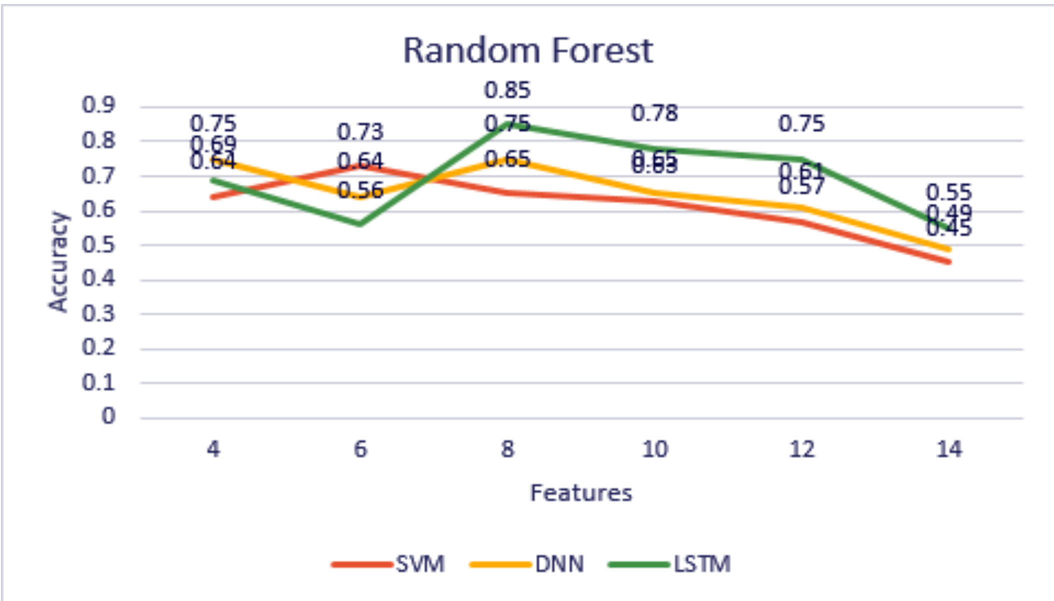

Figure 4.1: Analysis of classification Model using Random Forest

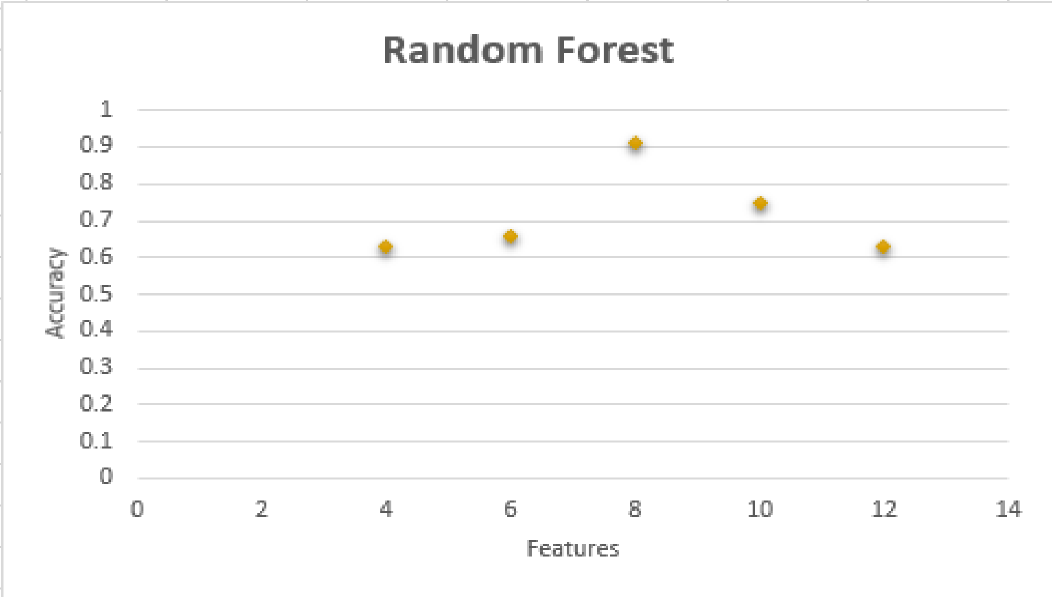

Figure 4.2: Analysis of features using Random Forest

4.3.3 Results of Recursive Feature Elimination

Analysis of important features of different classification models using Recursive feature elimination. It gives different accuracy results in different features shown in figure(4.3)

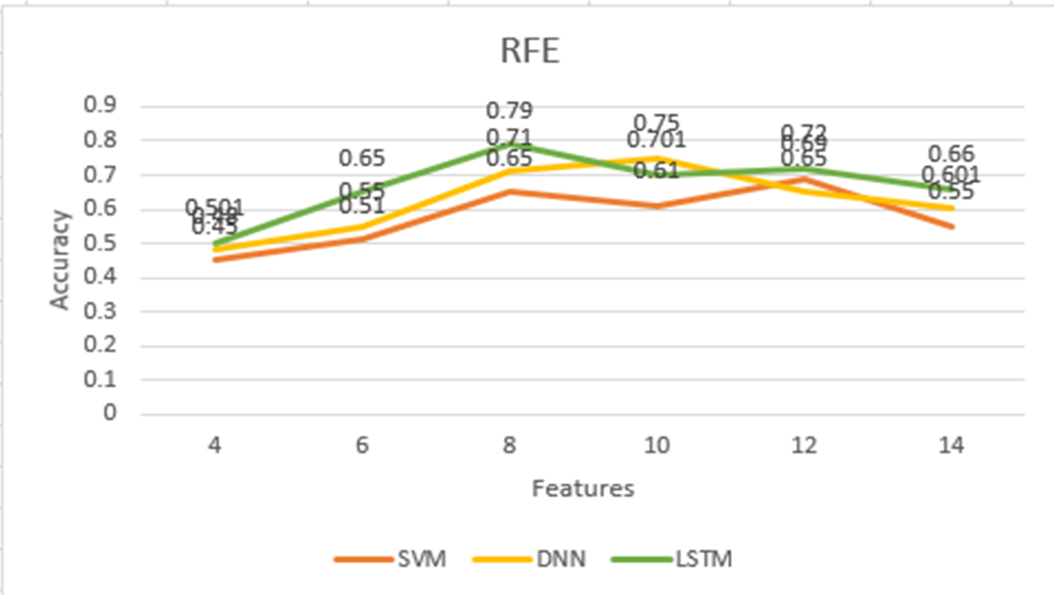

Figure 4.3: Analysis of Classification Model using Recursive Feature Elimination

Importance measure of each variables using Recursive Feature Elimination

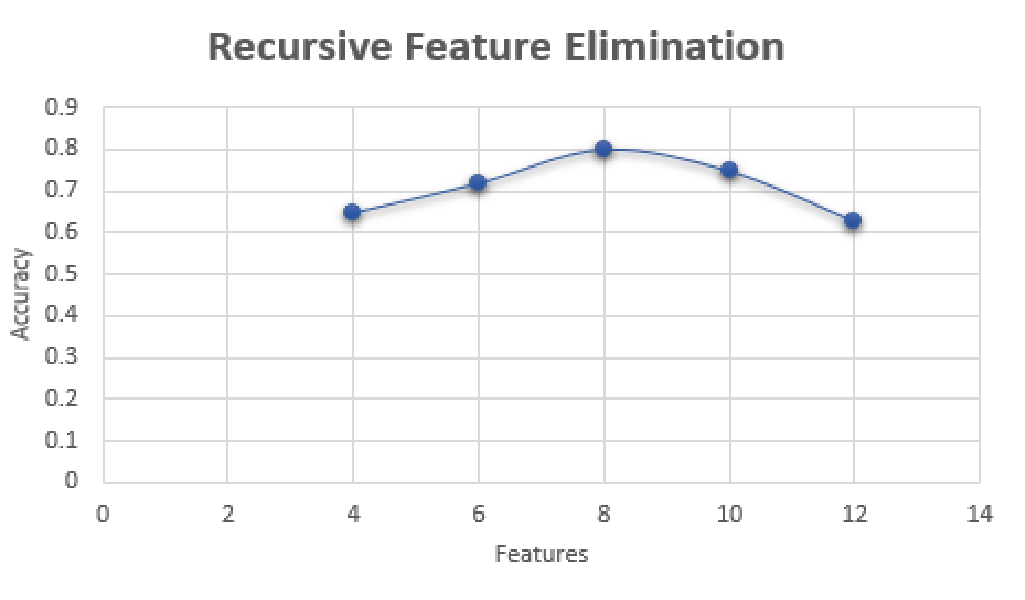

Figure 4.4: Analysis of features using Recursive Feature Method

4.3.4 Results of SelectkBest

Analysis of important features of classification models using Selectkbest.It gives different accuracy result in a different range of features. It shows the highest accuracy on features shown below (Figure 4.5)

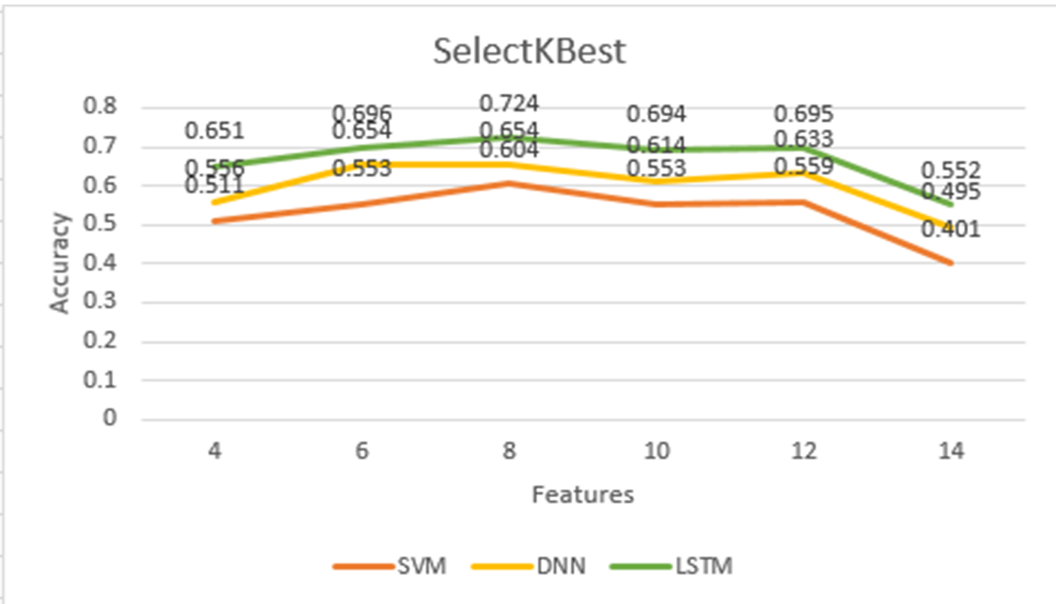

Figure 4.5: Analysis of features using SelectKBest Method

4.3.5 Correlation Matrix

For the analytical model, we used the correlation matrix based on features. Correlation matrix shows the features in positive and negative values.

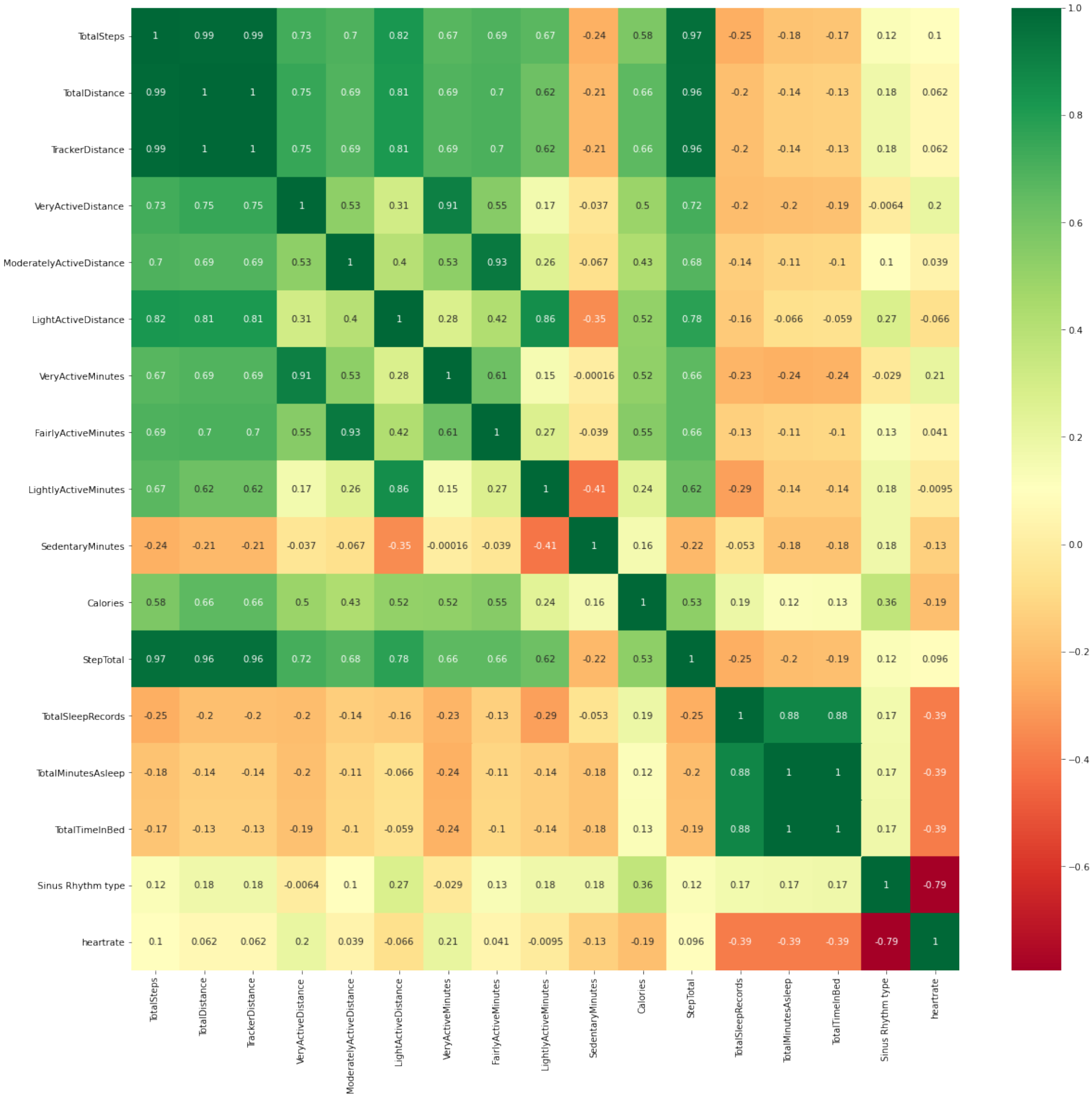

Figure 4.6: Correlation Matrix based on relative importance features

In our case, Heartrate correlated with other features such as sinus rhythm type gives highly correlated.

4.3.6 Comparison with other methods

For the comparison with different models , we compare the different model performance with our system.The comparison show as follow in Table:4.2.Dijkhuis et al. works in 2018 [74] using Random forest classifier obtained 0.73% accuracy respectively.

Aarti Sathyanarayana et al. works in 2016 using CNN classifier which obtained 0.64% accuracy.The proposed system obtained the accuracy up to 0.85%.

Table 4.2: Comparison accuracies with other methods

Study	**Classifier**	**Accuracy**
Dijkhuis et al.,(2018) [74]	RF	0.73%
Aarti Sathyanarayana et al.(2016) [82]	CNN	0.64 %
Proposed	**LSTM**	**0.85** %

4.4 Summary

The section presents the details of the different experiments with the results which we performed. We use the different classification models and selection features for the experiment and got the results shown in above table 4.1. Overall we achieved accuracy up to 0.85%.

CHAPTER 5

CONCLUSION & FUTURE WORK

Wearable devices play a vital part in the health care and monitoring system. Wearable tracker research has been vigorously centered around by the scholarly community lately, including endeavors to survey wellness, rest, heart wellbeing, general prosperity, recovery from clinical diseases, and so on.

Fitbit and other fitness watches play a vital role in the health monitoring system. It is useful and less costly as compared to other systems. Every age of people use Fitbit, and other fitness watches for health purposes. Fitbit tracks the daily activities like the number of steps while walking, sleep hours, minutes, how much calories burned, heart rate, and so on.

This study used three classification models, SVM, DNN, and LSTM, with three feature selection methods such as filter method (SelectkBest), Recursive feature elimination, and random forest classifiers Fitbit dataset. Recently, Fitbit trackers and other fitness watches are a significant part of a healthy and active life. We took the best features through the random forest method (RF), which gave us the best results based on accuracy compared to other classifiers. Random Forest gives us up to 85% accuracy with eight best features.

For future work, combine the classification models with different selection methods for better results. Take a larger dataset and different data repositories.

REFERENCES

[1] Y. Gu, J. Shen, Y. Chen, Poster abstract: Know you better: a smart watch based health monitoring system, in: 2019 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE), 2019, pp. 7–8.

[2] K. Lin, F. Xia, W. Wang, D. Tian, J. Song, System design for big data application in emotion-aware healthcare, IEEE Access 4 (2016) 6901–6909.

[3] H. Li, J. Wu, Y. Gao, Y. Shi, Examining individuals' adoption of healthcare wearable devices: An empirical study from privacy calculus perspective (Jan 2016).

[4] M. Haghi, K. Thurow, R. Stoll, Wearable devices in medical internet of things: Scientific research and commercially available devices, Healthcare Informatics Research 23 (1) 4.

[5] J. Hernandez, Y. Li, J. M. Rehg, R. W. Picard, Bioglass: Physiological parameter estimation using a head-mounted wearable device, in: 2014 4th International Conference on Wireless Mobile Communication and Healthcare - Transforming Healthcare Through Innovations in Mobile and Wireless Technologies (MOBIHEALTH), 2014, pp. 55–58.

[6] J. Wijsman, B. Grundlehner, H. Liu, H. Hermens, J. Penders, Towards mental stress detection using wearable physiological sensors, in: 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2011, pp. 1798–1801.

[7] D. Anzaldo, Wearable sports technology-market landscape and compute soc trends, 2015, pp. 217–218.

[8] S. Movassaghi, M. Abolhasan, J. Lipman, D. Smith, A. Jamalipour, Wireless body area networks: A survey, IEEE Communications Surveys Tutorials 16 (3) (2014) 1658–1686.

[9] Z. H. Jiang, Z. Cui, T. Yue, Y. Zhu, D. H. Werner, Compact, highly efficient, and fully flexible circularly polarized antenna enabled by silver nanowires for wireless body-area networks, IEEE Transactions on Biomedical Circuits and Systems 11 (4) (2017) 920–932.

[10] X. Yu, M. Paul, C. H. Antink, B. Venema, V. Blazek, C.Bollheimer, S. Leonhardt, b. p. y. D. Teichmann, title=Non-Contact Remote Measurement of Heart Rate Variability using Near-Infrared Photoplethysmography Imaging.

[11] G. Rebolledo-Mendez, A. Reyes, S. Paszkowicz, M. C. Domingo, L. Skrypchuk, Developing a body sensor network to detect emotions during driving, IEEE Transactions on Intelligent Transportation Systems 15 (4) (2014) 1850–1854.

[12] E. Kanjo, E. M. Younis, N. Sherkat, Towards unravelling the relationship between on-body, environmental and emotion data using sensor information fusion approach, Information Fusion 40 (2018) 18–31.

[13] O. Banos, R. Garcia, J. A. Holgado-Terriza, M. Damas, H. Pomares, I. Rojas, A. Saez, C. Villalonga, mhealthdroid: A novel framework for agile development of mobile health applications, Ambient Assisted Living and Daily Activities Lecture Notes in Computer Science (2014) 91–98.

[14] D. L. Hall, J. Llinas, An introduction to multisensor data fusion, Proceedings of the IEEE 85 (1) (1997) 6–23.

[15] S.-H. Hwang, E.-H. Kim, An approach for mining folksonomies based on the triadic class hierarchies, Advanced Science Letters 9 (2012) 844–849.

[16] K. Shihab, A backpropagation neural network for computer network security, Journal of Computer Science 2 (9) (2006) 710–715.

[17] S. R. Jeffery, G. Alonso, M. J. Franklin, W. Hong, J. Widom, Declarative support for sensor data cleaning, Lecture Notes in Computer Science Pervasive Computing (2006) 83–100.

[18] Y. B. Kim, D. Kim, Healthcare service with ubiquitous sensor networks for the disabled and elderly people, Lecture Notes in Computer Science Computers Helping People with Special Needs (2006) 716–723.

[19] S. Kalamkar, G. Mary A., Clinical data fusion and machine learning techniques for smart healthcare, in: 2020 International Conference on Industry 4.0 Technology (I4Tech), 2020, pp. 211–216.

[20] Z.-X. Li, Y.-G. Ma, A new method of multi-sensor information fusion based on svm, 2009 International Conference on Machine Learning and Cybernetics (2009).

[21] M. Muzammal, R. Talat, A. H. Sodhro, S. Pirbhulal, A multi-sensor data fusion enabled ensemble approach for medical data from body sensor networks, Information Fusion 53 (2020) 155–164.

[22] A. Sathyanarayana, S. Joty, L. Fernandez-Luque, F. Ofli, J. Srivastava, A. Elmagarmid, T. Arora, S. Taheri, Sleep quality prediction from wearable data using deep learning, JMIR mHealth and uHealth 4 (4) (2016) 125.

[23] Z. J. Yürüten, O., P. Pu, Decomposing activities of daily living to discover routine clusters, AAAI Conference on Artificial Intelligence (2014) 1348–1354.

[24] S. Chandra, Iot for wearable devices: access control and identity management, Wearable Sensors:Applications, design and implementation (2017).

[25] W. Zhou, S. Piramuthu, Security/privacy of wearable fitness tracking iot devices, in: 2014 9th Iberian Conference on Information Systems and Technologies (CISTI), 2014, pp. 1–5.

[26] I. Tucker, Five of the best health monitoring devices (2016).

[27] S.Draper, Top 7 affordable fitbit alternatives to help you stay fit and save money, Wearable Technologies (2018).
URL `https://www.wearable-technologies.com/2018/07/top-7-affordable-fitbit-alternatives-to-help-you-stay-fit-and-save-money/`

[28] M. M. Baig, H. Gholamhosseini, Smart health monitoring systems: An overview of design and modeling, Journal of Medical Systems 37 (2) (2013).

[29] M. Chan, D. Estève, J.-Y. Fourniols, C. Escriba, E. Campo, Smart wearable systems: Current status and future challenges, Artificial Intelligence in Medicine 56 (3) (2012) 137–156.

[30] R. Bellazzi, F. Ferrazzi, L. Sacchi, Predictive data mining in clinical medicine: a focus on selected methods and applications, Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 1 (5) (2011) 416–430.

[31] L. Atallah, B. Lo, G.-Z. Yang, Can pervasive sensing address current challenges in global healthcare?, Journal of Epidemiology and Global Health 2 (1) (2012) 1.

[32] V. Nangalia, D. R. Prytherch, G. B. Smith, Health technology assessment review: Remote monitoring of vital signs - current status and future challenges, Critical Care 14 (5) (2010) 233.

[33] M. Kalantari, "consumers' adoption of wearable technologies: Literature review, synthesis, and future research agenda.", nternational Journal of Technology Marketing 12 (2017).

[34] M. Dehghani, Exploring the motivational factors on continuous usage intention of smartwatches among actual users, Behaviour amp; Information Technology 37 (2) (2018) 145–158.

[35] S. H.-W. Chuah, P. A. Rauschnabel, N. Krey, B. Nguyen, T. Ramayah, S. Lade, Wearable technologies: The role of usefulness and visibility in smartwatch adoption, Computers in Human Behavior 65 (2016) 276–284.

[36] M. Aminian, A hospital healthcare monitoring system using wireless sensor networks, Journal of Health amp; Medical Informatics 04 (02) (2013).

[37] J. Edwards, Wireless sensors relay medical insight to patients and caregivers [special reports], IEEE Signal Processing Magazine 29 (3) (2012) 8–12.

[38] K. Malhi, S. C. Mukhopadhyay, J. Schnepper, M. Haefke, H. Ewald, A zigbee-based wearable physiological parameters monitoring system, IEEE Sensors Journal 12 (3) (2012) 423–430.

[39] P. A. Shaltis, A. T. Reisner, H. H. Asada, Cuffless blood pressure monitoring using hydrostatic pressure changes, IEEE Transactions on Biomedical Engineering 55 (6) (2008) 1775–1777.

[40] M. Poh, K. Kim, A. Goessling, N. Swenson, R. Picard, Cardiovascular monitoring using earphones and a mobile device, IEEE Pervasive Computing 11 (4) (2012) 18–26.

[41] P. Salvo, F. Di Francesco, D. Costanzo, C. Ferrari, M. G. Trivella, D. De Rossi, A wearable sensor for measuring sweat rate, IEEE Sensors Journal 10 (10) (2010) 1557–1558.

[42] B. Chen, S. Patel, T. Buckley, R. Rednic, D. J. McClure, L. Shih, D. Tarsy, M. Welsh, P. Bonato, A web-based system for home monitoring of patients with parkinson's disease using wearable sensors, IEEE Transactions on Biomedical Engineering 58 (3) (2011) 831–836.

[43] S. Patel, K. Lorincz, R. Hughes, N. Huggins, J. Growdon, D. Standaert, M. Akay, J. Dy, M. Welsh, P. Bonato, Monitoring motor fluctuations in patients with parkinson's disease using wearable sensors, IEEE Transactions on Information Technology in Biomedicine 13 (6) (2009) 864–873.

[44] P. Castillejo, J. Martinez, J. Rodriguez-Molina, A. Cuerva, Integration of wearable devices in a wireless sensor network for an e-health application, IEEE Wireless Communications 20 (4) (2013) 38–49.

[45] O. Aziz, S. N. Robinovitch, An analysis of the accuracy of wearable sensors for classifying the causes of falls in humans, IEEE Transactions on Neural Systems and Rehabilitation Engineering 19 (6) (2011) 670–676.

[46] T. Shany, S. J. Redmond, M. R. Narayanan, N. H. Lovell, Sensors-based wearable systems for monitoring of human movement and falls, IEEE Sensors Journal 12 (3) (2012) 658–670.

[47] A. A. A. Timmermans, H. A. M. Seelen, R. P. J. Geers, P. K. Saini, S. Winter, J. T. Vrugt, H. Kingma, Sensor-based arm skill training in chronic stroke patients: Results on treatment outcome, patient motivation, and system usability, IEEE Transactions on Neural Systems and Rehabilitation Engineering 18 (3) (2010) 284–292.

[48] R. Rednic, E. Gaura, J. Brusey, J. Kemp, Wearable posture recognition systems: Factors affecting performance, in: Proceedings of 2012 IEEE-EMBS International Conference on Biomedical and Health Informatics, 2012, pp. 200–203.

[49] A. Huang, W. Xu, Z. Li, L. Xie, M. Sarrafzadeh, X. Li, J. Cong, System light-loading technology for mhealth: Manifold-learning-based medical data cleansing and clinical trials in we-care project, IEEE Journal of Biomedical and Health Informatics 18 (5) (2014) 1581–1589.

[50] J. Y. Xu, H. Chang, C. Chien, W. J. Kaiser, G. J. Pottie, Context-driven, prescription-based personal activity classification: Methodology, architecture, and end-to-end implementation, IEEE Journal of Biomedical and Health Informatics 18 (3) (2014) 1015–1025.

[51] N. Alshurafa, H. Kalantarian, M. Pourhomayoun, S. Sarin, J. J. Liu, M. Sarrafzadeh, Non-invasive monitoring of eating behavior using spectrogram analysis in a wearable necklace, in: 2014 IEEE Healthcare Innovation Conference (HIC), 2014, pp. 71–74.

[52] M. Giuberti, G. Ferrari, L. Contin, V. Cimolin, C. Azzaro, G. Albani, A. Mauro, Automatic updrs evaluation in the sit-to-stand task of parkinsonians: Kinematic analysis and comparative outlook on the leg agility task, IEEE Journal of Biomedical and Health Informatics 19 (3) (2015) 803–814.

[53] J. Gong, J. Lach, Y. Qi, M. D. Goldman, Causal analysis of inertial body sensors for enhancing gait assessment separability towards multiple sclerosis diagnosis, in: 2015 IEEE 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN), 2015, pp. 1–6.

[54] J. Y. Xu, Y. Wang, M. Barrett, B. Dobkin, G. J. Pottie, W. J. Kaiser, Personalized multilayer daily life profiling through context enabled activity classification and motion reconstruction: An integrated system approach, IEEE Journal of Biomedical and Health Informatics 20 (1) (2016) 177–188.

[55] J. Gong, Y. Qi, M. D. Goldman, J. Lach, Causality analysis of inertial body sensors for multiple sclerosis diagnostic enhancement, IEEE Journal of Biomedical and Health Informatics 20 (5) (2016) 1273–1280.

[56] T. Nakamura, V. Goverdovsky, M. J. Morrell, D. P. Mandic, Automatic sleep monitoring using ear-eeg, IEEE Journal of Translational Engineering in Health and Medicine 5 (2017) 1–8.

[57] D. Naranjo-Hernández, A. Talaminos-Barroso, J. Reina-Tosina, L. Roa, G. Barbarov-Rostan, P. Cejudo-Ramos, E. Márquez-Martín, F. Ortega-Ruiz, Smart vest for respiratory rate monitoring of copd patients based on non-contact capacitive sensing, Sensors 18 (7) (2018) 2144.

[58] A. Kuusik, M. M. Alam, T. Kask, K. Gross-Paju, Wearable m-assessment system for neurological disease patients, in: 2018 IEEE 4th World Forum on Internet of Things (WF-IoT), 2018, pp. 201–206.

[59] P. Sok, T. Xiao, Y. Azeze, A. Jayaraman, M. V. Albert, Activity recognition for incomplete spinal cord injury subjects using hidden markov models, IEEE Sensors Journal 18 (15) (2018) 6369–6374.

[60] S. Haghayegh, S. Khoshnevis, M. H. Smolensky, K. R. Diller, R. J. Castriotta, Accuracy of wristband fitbit models in assessing sleep: Systematic review and meta-analysis, Journal of Medical Internet Research 21 (11) (2019).

[61] X. Yu, S. Wang, A health check and prediction system for lifestyle-related disease prevention, First International Conference on Innovative Computing, Information and Control - Volume I (ICICIC'06).

[62] N. Martini, D. Menicucci, L. Sebastiani, R. Bedini, A. Pingitore, N. Vanello, M. Milanesi, L. Landini, A. Gemignani, The dynamics of eeg gamma responses to unpleasant visual stimuli: From local activity to functional connectivity, NeuroImage 60 (2) (2012) 922–932.

[63] R. Gravina, G. Fortino, Automatic methods for the detection of accelerative cardiac defense response, IEEE Transactions on Affective Computing 7 (3) (2016) 286–298.

[64] I. Kadi, A. Idri, J. Fernandez-Aleman, Knowledge discovery in cardiology: A systematic literature review, International Journal of Medical Informatics 97 (2017) 12–32.

[65] S. Sneha, U. Varshney, Enabling ubiquitous patient monitoring: Model, decision protocols, opportunities and challenges, Decision Support Systems 46 (3) (2009) 606–619.

[66] A. Pantelopoulos, N. Bourbakis, A survey on wearable sensor-based systems for health monitoring and prognosis, IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews) 40 (1) (2010) 1–12.

[67] S. Benedetto, C. Caldato, E. Bazzan, D. C. Greenwood, V. Pensabene, P. Actis, Assessment of the fitbit charge 2 for monitoring heart rate, PLOS ONE 13 (2) (2018) e0192691.

[68] G. Nazari, J. C. Macdermid, K. E. Sinden, J. Richardson, A. Tang, Reliability of zephyr bioharness and fitbit charge measures of heart rate and activity at rest, during the modified canadian aerobic fitness test, and recovery, Journal of Strength and Conditioning Research 33 (2) (2019) 559–571.

[69] S. P. Wright, T. S. Hall Brown, S. R. Collier, K. Sandberg, How consumer physical activity monitors could transform human physiology research, American Journal of Physiology-Regulatory, Integrative and Comparative Physiology 312 (3) (2017) R358–R367.

[70] D. Valbuena, B. G. Miller, A. L. Samaha, R. G. Miltenberger, Data presentation options to manage variability in physical activity research, Journal of Applied Behavior Analysis 50 (3) (2017) 622–640.

[71] F. Chamroukhi, S. Mohammed, D. Trabelsi, L. Oukhellou, Y. Amirat, Joint segmentation of multivariate time series with hidden process regression for human activity recognition, Neurocomputing 120 (2013) 633–644.

[72] G. Sprint, D. Cook, D. Weeks, J. Dahmen, A. L. Fleur, Analyzing sensor-based time series data to track changes in physical activity during inpatient rehabilitation, Sensors 17 (10) (2017) 2219.

[73] S. S. Phatak, M. T. Freigoun, C. A. Martín, D. E. Rivera, E. V. Korinek, M. A. Adams, M. P. Buman, P. Klasnja, E. B. Hekler, Modeling individual differences: A case study of the application of system identification for personalizing a physical activity intervention, Journal of Biomedical Informatics 79 (2018) 82–97.

[74] T. B. Dijkhuis, F. J. Blaauw, M. W. van Ittersum, H. Velthuijsen, M. Aiello, Personalized physical activity coaching: A machine learning approach, Sensors 18 (2) (2018) 623.

[75] T. Choksatchawathi, P. Ponglertnapakorn, A. Ditthapron, P. Leelaarporn, T. Wisutthisen, M. Piriyajitakonkij, T. Wilaiprasitporn, Improving heart rate estimation on consumer grade wrist-worn device using post-calibration approach, IEEE Sensors Journal 20 (13) (2020) 7433–7446.

[76] A. Almogbil, A. Alghofaili, C. Deane, T. Leschke, A. Almogbil, A. Alghofaili, The accuracy of gps-enabled fitbit activities as evidence: A digital forensics study, in: 2020 7th IEEE International Conference on Cyber Security and Cloud Computing (CSCloud)/2020 6th IEEE International Conference on Edge Computing and Scalable Cloud (EdgeCom), 2020, pp. 186–189.

[77] MacDermott, S. Lea, F. Iqbal, I. Idowu, B. Shah, Forensic analysis of wearable devices: Fitbit, garmin and hetp watches, in: 2019 10th IFIP International Conference on New Technologies, Mobility and Security (NTMS), 2019, pp. 1–6.

[78] Z. Liang, M. A. Chapa-Martell, Combining resampling and machine learning to improve sleep-wake detection of fitbit wristbands, in: 2019 IEEE International Conference on Healthcare Informatics (ICHI), 2019, pp. 1–3.

[79] Z. Liang, T. Nishimura, Are wearable eeg devices more accurate than fitness wristbands for home sleep tracking? comparison of consumer sleep trackers with clinical devices, in: 2017 IEEE 6th Global Conference on Consumer Electronics (GCCE), 2017, pp. 1–5.

[80] G. M. Weiss, J. W. Lockhart, T. T. Pulickal, P. T. McHugh, I. H. Ronan, J. L. Timko, Actitracker: A smartphone-based activity recognition system for improving health and well-being, in: 2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA), 2016, pp. 682–688.

[81] M. Rahman, B. Carbunar, U. Topkara, Secure management of low power fitness trackers, IEEE Transactions on Mobile Computing 15 (2) (2016) 447–459.

[82] A. Sathyanarayana, S. Joty, L. Fernandez-Luque, F. Ofli, J. Srivastava, A. Elmagarmid, T. Arora, S. Taheri, Sleep quality prediction from wearable data using deep learning, JMIR Mhealth Uhealth 4 (4) (2016) e125.

[83] C. M. Lee, C. W. Jung, Radiation-pattern-reconfigurable antenna using monopole-loop for fitbit flex wristband, IEEE Antennas and Wireless Propagation Letters 14 (2015) 269–272.

[84] T. Tan, M. Gochoo, K. Chen, F. Jean, Y. Chen, F. Shih, C. F. Ho, Indoor activity monitoring system for elderly using rfid and fitbit flex wristband, in: IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI), 2014, pp. 41–44.

[85] J. Brownlee, Feature selection for machine learning in python (Aug 2020). URL `https://machinelearningmastery.com/feature-selection-machine- learning-python/`

[86] Z. M. Hira, D. F. Gillies, A review of feature selection and feature extraction methods applied on microarray data, Advances in Bioinformatics 2015 (2015) 1–13.

[87] M. Raihan-Al-Masud, M. R. H. Mondal, Data-driven diagnosis of spinal abnormalities using feature selection and machine learning algorithms, Plos One 15 (2) (2020).

APPENDIX A

APPENDIX ONE

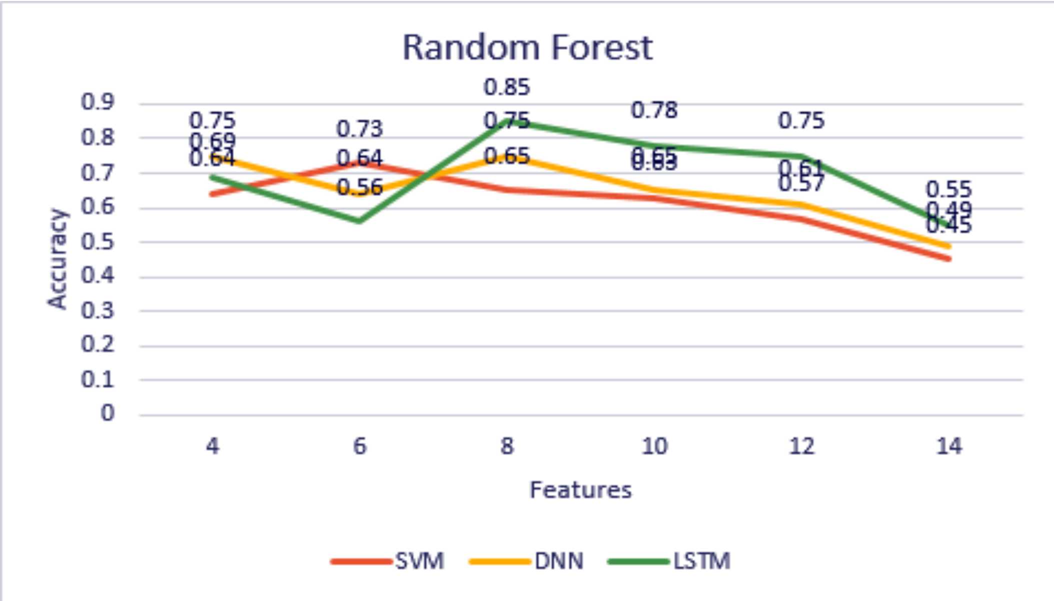

Figure A.1: Analysis of classification Model using Random Forest

APPENDIX B

APPENDIX TWO

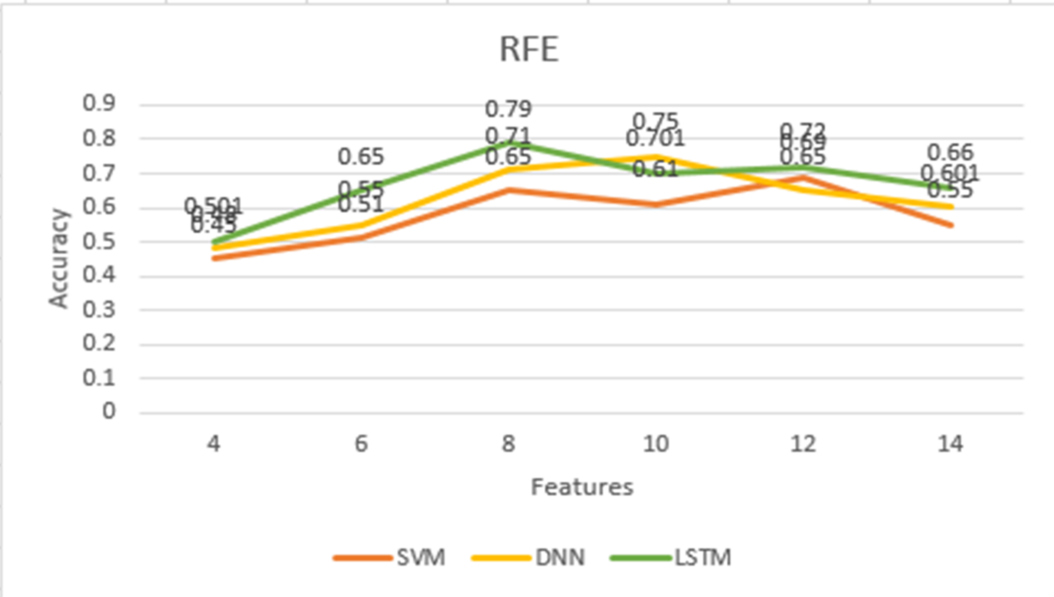

Figure B.1: Analysis of Classification Model using Recursive Feature Elimination

APPENDIX C

APPENDIX THREE

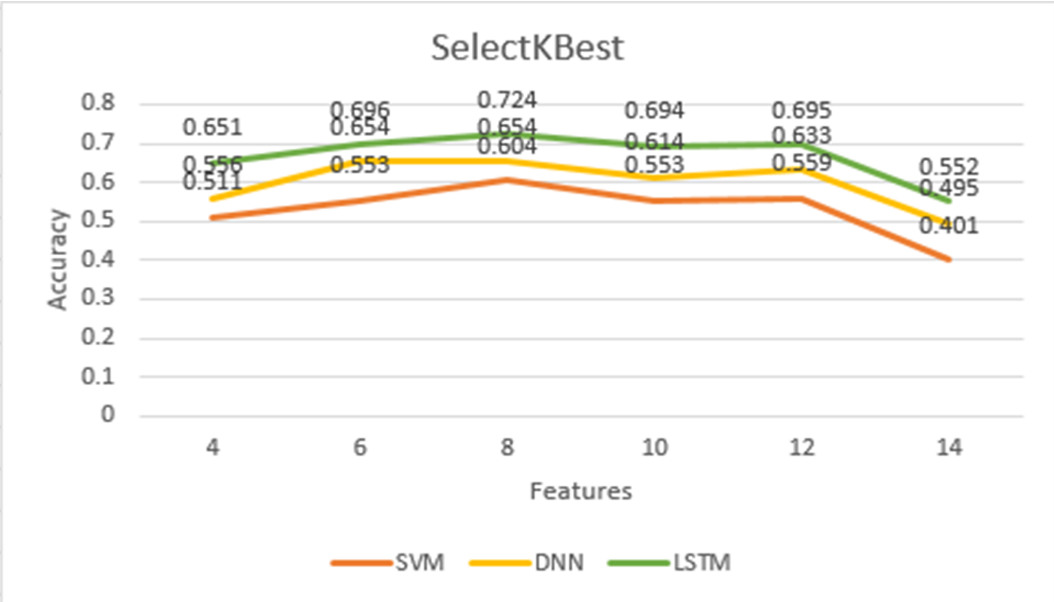

Figure C.1: Analysis of features using SelectKBest Method

APPENDIX D

APPENDIX FOUR

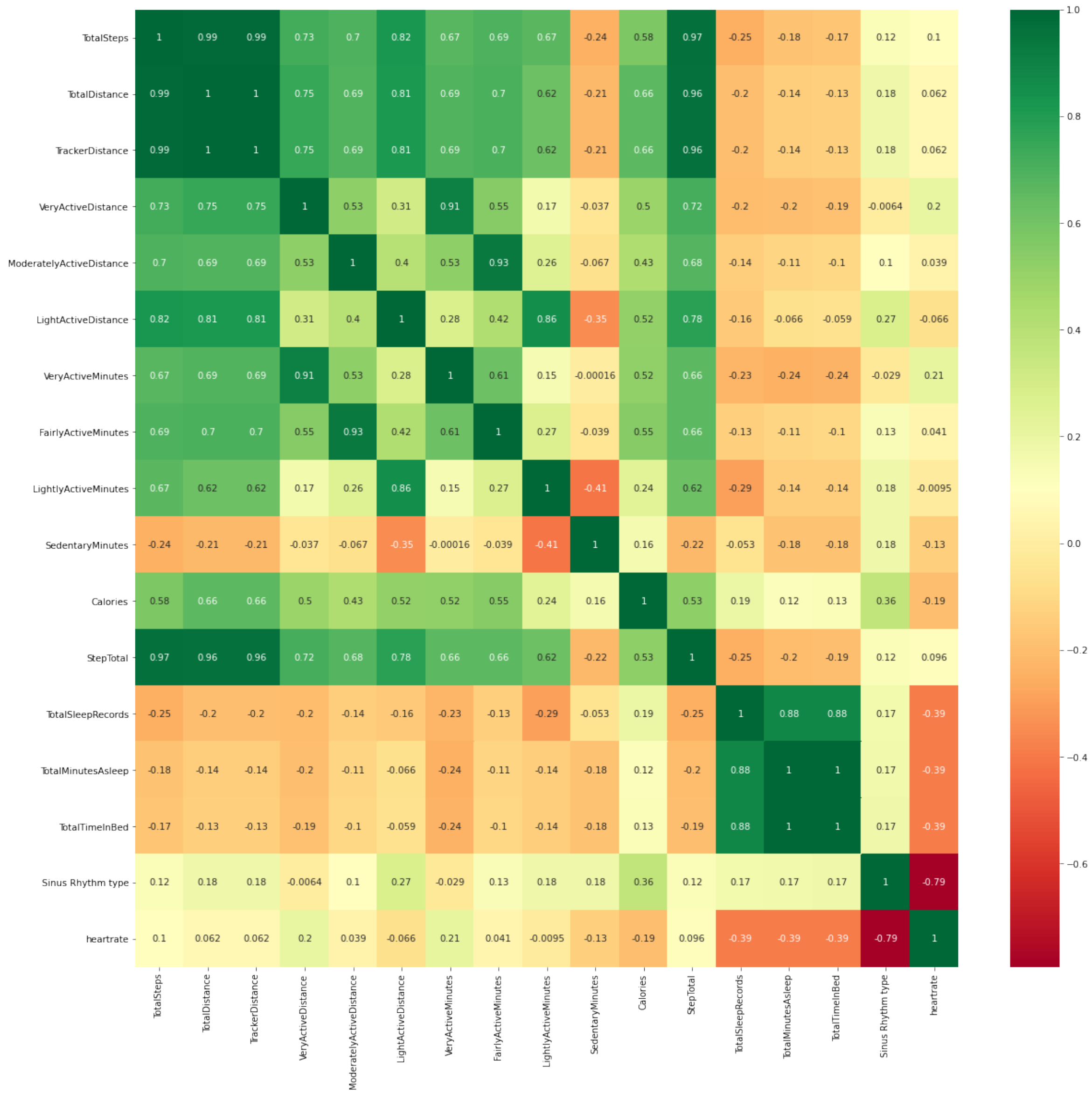

Figure D.1: Correlation Matrix based on relative importance features