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Fall incidence prediction system for elderly people based on IoT and classification techniques

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ABSTRACT

Health monitoring systems based on the internet of things (IoT) improve patient well-being and reduce mortality risks. Machine learning techniques are most helpful in early fall prediction and detection. In this paper, fall prediction analysis and decision-making are done with existing benchmark clinical records. Classification techniques are incorporated to track the consistency and precision of data acquired by the IoT-based remote health monitoring for elderly people, especially those who are living alone. This work undertakes two approaches to early predicting a patient's acute illness. The first approach has analyzed the existing benchmark patient activity data with different features. This approach builds the classification model for fall incidence with the help of machine learning models. In second approach, we collect real-time sensor data such as blood pressure and heart rate from IoT sensor gadgets which are transmitted to the prediction model for early prediction. Experimental results prove that the random forest (RF) classifiers and XGBoost provides the maximum accuracy.

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1. INTRODUCTION

Nowadays, the internet of things (IoT) brought a major revolution in the healthcare sector. The whole market is shifting its trajectory from the capacity to remote tracking, utilizing smart sensors and integrating clinical equipment. The major advantages of IoT-based patient monitoring systems are improvement in persistent health security and relatively better physician-patient involvement. The acute illness (fall detection) of elderly people whose age is above 60 years may lead to fatal injury. This is a significant challenge in elderly people's life. Over the past few years, researchers proposed various approaches in the field of fall detection, which are characterized by the following three categories; there are wearable sensor-based fall detection, environment sensor-based fall-detection, and image/video-based fall-detection [1].

Wearable sensor devices like a magnetometer and accelerometers identify the geographical location and activity of the individual [2]. The expense of these wearable sensor-based devices is exceptionally low, and working techniques are not hard for older people. The environmental sensor-based methodology consistently utilizes sensors in the identification and screening of the human body [3]. This is a cheap and simple method to utilize. However, detecting objects other than human bodies requires multiple tests of the exactness of this methodology. Image/video-based fall detection methodology utilizes camcorders to follow all particles inside the range, including human bodies [4]. Compared to the other two methodologies referenced above, this fall-detection procedure provides minimum interruption in an individual's day-to-day life, but surveillance space is limited to a certain range of distance. Accomplishing pervasive reconnaissance is not an easy task in this system.

Artificial intelligence and computer vision researchers are investigating how to recognize human falls automatically. According to the World Health Organization, falls are the second most common cause of unintentional injury and death among people aged 65 and older. The number of falls among people over age 65 ranges from 28-35%. The list of classification algorithms studied in this work is logistic regression (LR), k-nearest neighbors (KNN), naïve Bayes (NB), support vector machine (SVM), stochastic gradient decent (SGD), decision tree (DT), random forest (RF), and XGBoost (XGB). These classification methods are implemented in the early prediction of acute illness for elderly people, and these are compared using performance metrics. The performance metrics are accuracy, sensitivity, and specificity. This paper proposes a pioneer methodology for the early fall detection of older individuals with the help of physiological parameters [5]. The framework is based on the operating systems Arduino, ThingSpeak, and Windows 10. Raw data from physiological sensors like blood pressure (BP) and heart rate (HR) are sensed and collected in the Arduino board [6], [7].

2. RELATED WORK

Several machine-learning techniques are employed to detect fall detection over the years and are discussed in this section. Paredes *et al.* [8], proposed a method to develop a remotely accessible IoT-based non-invasive BP monitor. Applications of an IoT-enabled device allow access to remote areas in the hospital using remote monitoring and centralized surveillance. Shihab *et al.* [9], proposed to integrate digital blood pressure measuring devices with IoT using Arduino to process MPX 5050 dB sensor values. In addition, the author made a Firebase database access through the internet connection using NodeMCU. But despite Firebase's performance, this IoT network serial communication from experiences some setbacks and time delays from Arduino to Node. Neto *et al.* in [10], proposed a methodology utilizing IoT innovations in the observation of stationary individuals who need complete consideration. The system monitors users physiological aspects through devices that are portable and wearable device that sends the collected data to a cloud system. Utekar and Umale [11], proposed an automated IoT-based healthcare system to monitor patients remotely. Updating patient health parameters from time to time for physicians can become a big issue. The system sends email alerts to indicate abnormalities. Results were analyzed for the abnormalities of health parameters and alerts when the operation situation is found to be dangerous.

Ahamed and Farid [12], proposed personalized healthcare using IoT with machine learning and discussed the limitations and challenges of personalized health systems. In the research trends, some standards of machine learning models reported consistent problems which need major focus. Islam *et al.* [13], presented a comprehensive survey on the IoT for healthcare. The survey recorded advances in IoT-based medical services innovations and surveys on modern and potential organization design, applications, and industry drifts in IoT-based medical care arrangements. Furthermore, the study offered an assortment of network constructions and phases that help admittance to the IoT spine that encourages the exchange and gathering of clinical information. Noury *et al.* [14], proposed fall-detection principles and methods with an extensive review of frameworks, systems, and sensors that naturally identify acute illness in aged people. Chen *et al.* [15], described wearable sensors in the prediction of acute illness with geographical location. The MEMS accelerometers detect the sudden illness of an individual, and RF signal strength identifies the location.

Fall detection frameworks with wearable sensors are illustrated using cell phones [16]. Chung *et al.* [17], proposed the wearable ubiquitous healthcare monitoring system using IEEE 802.15.4 for transmitting physiological data from on-body wearable sensors to a base station. Kangas *et al.* [18], evaluated different algorithms for detecting sudden illness with minimal complexity using tri-axial accelerometers which are attached to the waist, wrist, and head of an individual. Mehmood *et al.* [19], contemplated a presentation about the classification of advanced daily life activities using the SHIMMER sensor dataset. Villaseñor *et al.* [20], illustrated the up-fall detection database with a multimodal approach. The database were consolidated, and valuable data bundles were recuperated from 17 youngsters who performed 11 exercises and were down suddenly on earth due to giddiness/weakness with no previous ailments. Vallabh *et al.* [21], illustrated fall detection using the mobifall dataset. They obtained an overall accuracy of 87.5% using the k-nearest neighbors algorithm. Evaluated based on their sensitivity of 90.70% and a specificity of 83.78%.

3. METHOD

Machine learning (ML) was developed in the early days of computing, where PCs can learn without being modified to do explicit learning. Lately, ML has been utilized for different medical care stages like disease identification, medical image diagnosis, drug discovery, and robotic surgical tools. Artificial intelligence (AI) programs use pre-ordered training datasets to classify future datasets based on a broad scope of algorithms. It is the process of perceiving, comprehending, and gathering thoughts into subgroups. An AI classifier anticipates the likelihood that future information will fit under the predetermined categories based on input processing.

3.1. Classification algorithms in machine learning

3.1.1. Decision tree

DT is a non-parametric supervised learning procedure that can be used for both classification and regression problems. However, the decision tree classification technique is the most frequently used application [22]. It has a tree structure classifier; there are four types of nodes in the hierarchy: roots, branches, internal nodes, and leaves. A tree starts from the root node and leads to the internal node. Branches address rules, and the end nodes are called a leaf.

3.1.2. Support vector machine

SVM algorithm is used to determine the best line or decision boundary in two-dimensional space. That boundary line is separated into classes to position new data sources in the correct segment. This ideal end range is known as the hyperplane.

3.1.3. Random forest

RF is a classifier with numerous decision trees in various subgroups of a given dataset to the prescient exactness of that data set. The main advantage of the RF algorithm is that it can handle data sets containing both continuous and categorical variables. As a result of RF, multiple decision trees are blended together in order to reach a single decision.

3.1.4. Logistic regression

LR is a basic regression model for categorical data to investigate the impact of the independent variable and a categorical dependent variable. This model used a logistic or logit model to evaluate the relationships between variables and a straight-out subordinate variable. These models predict the likelihood of events or events by fitting data to logistic curves [23]. The LR is a piece of a bigger class of algorithms known as the summed-up linear model. It is one of the measurable strategies for the relationship among variables.

3.1.5. Stochastic gradient decent

SGD is a class of AI algorithms appropriate for the enormous scope of learning. It is a proficient methodology for discriminative learning of linear classifiers below the work, which are direct SVM and LR. The SGD is applied to the enormous scope of AI issues that are available in text classification and different zones of natural language processing.

3.1.6. XGBoost

The XGBoost (XGB) library is a highly effective, adaptable, and compact dispersed gradient boosting library. The gradient boosting system is used to implement AI algorithms. With XGB, it handles numerous data science issues quickly and efficiently using equal tree boosting (also known as gradient boosting decision tree (GBDT) or gradient boosting machines (GBM)). The same code can handle billions of issues in a major appropriate environment (Hadoop, sun grid engine (SGE), and message passing interface (MPI)).

3.1.7. K-nearest neighbors

The KNN is one of the most straightforward supervised learning techniques. It expects the similitude between the new information and accessible classes and places the new information into the class that is generally like the accessible classes or categories. This is a non-parametric algorithm where no assumptions are made regarding hidden data. Additionally, it is known as a lazy learner algorithm since it does not gain knowledge from the training set quickly but rather stores the data for classification and plays out an activity at the appropriate moment.

3.1.8. NB classifier
An algorithm that relies solely on the Bayesian hypothesis is known as a NB classifier. This exceptionally valuable algorithm is for huge data indexes. With effortlessness, NB is preferred in most complex classification techniques. An algorithm that relies solely on the Bayesian hypothesis is known as a naïve Bayes classifier. This exceptionally valuable algorithm is for huge data indexes. With effortlessness, naïve Bayes is preferred in most complex classification techniques.

3.2. Arduino IDE software
As an integrated development tool, an Arduino IDE is a piece of open-source software that can be used to write code on an Arduino board and upload it to the board with the Arduino IDE. In addition to being compatible with multiple operating systems, the IDE application can also be downloaded on Mac OS X, Linux, and Windows computers. C and C++ are the two languages that are supported by it. Arduino IDE is presented for Arduino devices and allows programming the Arduino microcontrollers for connecting sensors and other types of components and performing operations both locally and globally through libraries.

3.3. Arduino blood pressure and heart rate sensor
Several research works are available for fall detection. Fall detection uses accelerometer data or vision-based data to detect a person who has fallen under acute illness. This limitation is a major challenge. Therefore, early fall detection using physiological parameters is proposed using a heart sensor and blood pressure sensor. Figure 1 shows the BP monitor connection with the Arduino board for analyzing the data.

3.4. ESP8266: a Wi-Fi module for IoT
In the IoT market, espressif systems produces the ESP8266 system on a chip (SOC). ESP8266 is now widely used across IoT devices due to its low cost, small size, and adaptability. It can be used with any microcontroller to access WiFi networks. With the ESP8266, you can either host an application or offload all Wi-Fi networking tasks to another processor. A microcontroller can be connected to 2.4 GHz Wi-Fi via the ESP8266 module using IEEE 802.11 standard. espressif systems-attention (ESP-AT) firmware provides connectivity to external host micro-controller units (MCUs) over Wi-Fi, and the module can also run an RTOS-based software development kit (SDK) to offer self-sufficient operation. This module has a full TCP/IP stack for data processing and can be controlled via general purpose input/output (GPIOs). Figure 2 shows the Arduino ESP8266 module.

Figure 1. Blood pressure and heart rate sensor

Figure 2. NodeMCU ESP8266 Wi-Fi development board

3.5. ThingSpeak IoT platform
ThingSpeak is also an IoT platform, in addition to collecting, visualizing, analyzing, and reacting to live data. The ioBridge was launched in 2010 as an open-source application. With it, one can build IoT systems without having to set up additional servers. For data collection, message queuing telemetry transport (MQTT) or representational state transfer (REST) application programming interface (API) keys were used. Analyzing and visualizing the data is done using MATLAB analytics [24]. The platform provides applications that allow users to perform various actions. Applications provided by ThingSpeak make it easy to integrate with web services, social networks, and other APIs.

4. PROPOSED WORK
To design and improvement of the IoT-based fall detection system for early fall detection for older adults. This problem statement is made with classification techniques using Python. A data collection phase is incorporated into two approaches in the proposed work. First one is collected existing benchmark clinical dataset from Chinese hospitals for old-age patient’s records. For better prediction accuracy, missing values are replaced with mean values as part of data analysis, a technique called data pre-processing. The data generated after pre-processing will be divided into two parts: 80% of training data and 20% of test data for

further analysis of early detection of falls using classification algorithms. Each attribute in Table 1 represents an entry in a different machine-learning algorithm. The second approach of proposed model incorporates data collection using IoT gadgets, and the implementation model includes the different key classification algorithms to predict early fall detection in this study. Figure 3 shows the functional module diagram of the task executed in this work. The user interface collects sensor data from the heart rate and blood pressure sensor. Physiological data is collected and transmitted to the intermediate device Aurdino Uno board using Bluetooth transfer media [25]. This data is transferred to the transitional gadget and shipped off the cloud as an exchange medium via WiFi. This data is further extracted from the cloud and transferred to a remote server for analysis [26]. In this work, data analysis includes detecting missing data for better prediction accuracy. On the remote server, the processed data are stored in a database. Also, that data is transferred to the classification model for further analysis. Figure 3 shows a prototype of the design and it comprises two principal sensors utilized for estimating BP and HR using mobile/PC applications. The fall detection is generated utilizing classification algorithms after data pre-processing.

Table 1 List of columns and their description

Columns	Description
ACTIVITY	Activity classification
TIME	Monitoring time
SL	Sugar level
EEG	EEG Monitoring rate
BP	Blood pressure
HR	Heart beat rate
CIRCULATION	Blood circulation

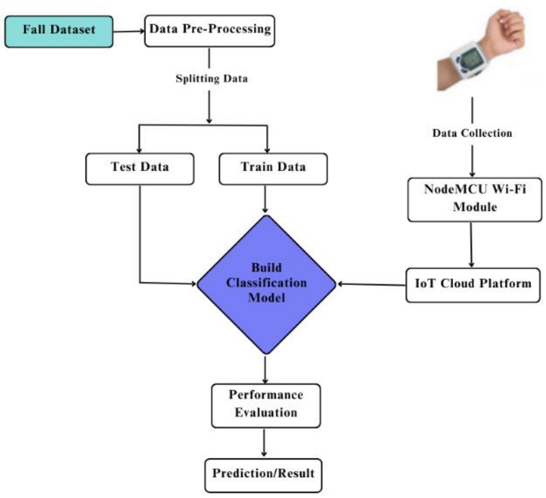


Figure 3. Design of the proposed model

5. RESULTS AND DISCUSSION

5.1. Data description

The dataset used in this work is the fall-detection dataset of Chinese hospitals for old-age patients downloaded from Kaggle. Next is a portrayal of the dataset, with two classes which are falling and not falling. This Chinese dataset has 16,382 instances (rows) and 7 attributes (columns). The columns with descriptions are mentioned in Table 1. The activity values for the given dataset are represented in Table 2.

Table 2 List of activities and their values

Values	Activity
0	Standing
1	Walking
2	Sitting
3	Falling
4	Cramps
5	Running

5.2. Pre-processed data

Raw data is derived from collected sensor data. A server is used to store this raw data, which is utilized for additional analysis using diverse classification algorithms. The work begins with collecting information from IoT sensor gadgets, then moving it to the cloud utilizing a WiFi connection, and gets moved to the server on a remote PC using an API key. The pre-processed data in work considers two parameters, for example, blood pressure (BP) and pulse sensor. The following pre-processed data consists of values for BP, heart rate (HR), and activity (target) for more than 16,000 people. Our goal is to predict how the person will fare when they fall, given their heart rate and blood pressure. Furthermore, the comparative analysis is also performed in order to provide a more complete picture. The pie chart for the activity of the patient is shown in Figure 4. According to Figure 4, 21.9% of patients are falling remaining are not falling. The full dataset contains a total of 3588 instances that have fallen activity. A major focus of the work is on the HR and BP data, where these two data are collected from individuals directly using IoT devices. The outlier in the activity data for HR and BP sensors is graphically depicted in Figures 5(a) and (b) respectively.

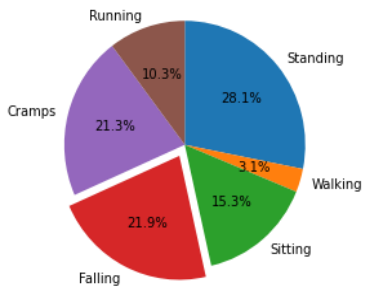
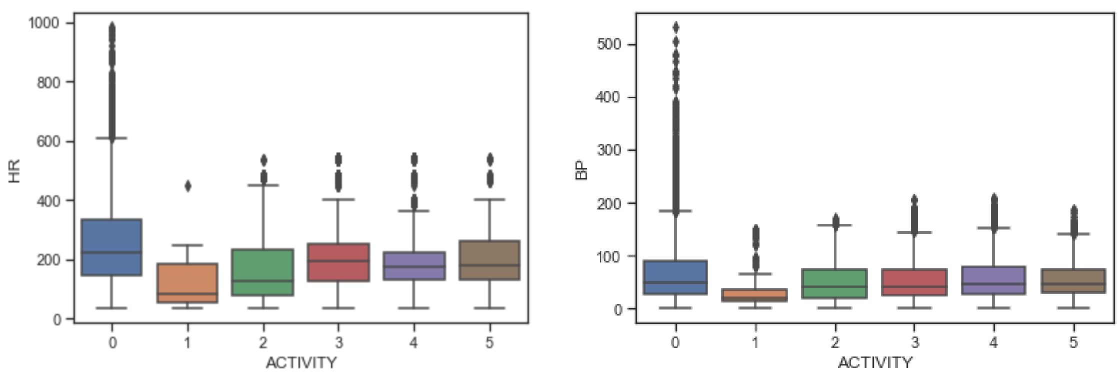


Figure 4. Composition of activity in the dataset

5.3. Performance metrics

This paper uses eight classification technique to model the early fall detection of elderly people using HR and BP sensor values. These techniques are KNN, SVM, RF, NB, SGD, DT, LR, and XGB. A comparison is made between these learning methods based on their accuracy in classifying objects. Moreover, precision, sensitivity, and specificity are likewise accommodated in these learning procedures. Table 3 provides measures of performance metrics.

When using the KNN algorithm to predict the value of any new data point, it utilizes the concept of feature similarity. As a result, a value is assigned to the new point based on how closely it resembles the points from the training set in terms of the similarity of the new point. Taking our training data into consideration, it finds instances that have a BP and HR similar to the existing instance's target value. This means the activity would also be similar to the training data's BP and HR. It can be demonstrated that all the proposals discussed above work to predict an individual's fall activity based on our sensor data, like KNN that has been mentioned before.



(a) (b)

Figure 5. An outlier in the: (a) HR and (b) BP

Table 3 Performance metrics

Performance metrics	Formula
Accuracy	TP+TN / TP+FP+FN+TN
Precision	TP / TP+FP
Sensitivity	TP / TP+FN
Specificity	TN / TN+FP

Table 4 shows that KNN and RF receive high scores compared with other machine learning classifiers. LR and NB obtain a minimum score of 77% result. Table 4 mentions mean accuracy; mean accuracy is repeated in each experiment 10 times, calculated from the overall accuracy. The results show the mean accuracy of each class. The mean accuracy of the RF classifier is high at about 87%. However, the SGD classifier gave a very minimum of 53% results. So, from the overall results, the RF classifier performs better for fall detection than other classifiers. Figure 6 shows the comparison of accuracy results using various ML classification techniques. The mean accuracy of the RF classifier is high at about 87%, and XGB resulted in a score of 86%. Therefore, from the overall results, the RF classifier and XGB classifier are performing better for fall detection compared with other classifiers.

Table 4. Accuracy results using machine learning techniques

Model	Score	Mean accuracy
LR	0.77	0.78
DT	0.76	0.82
KNN	0.82	0.83
NB	0.77	0.78
RF	0.82	0.87
SVM	0.78	0.78
SGD	0.78	0.53
XGB	0.80	0.86

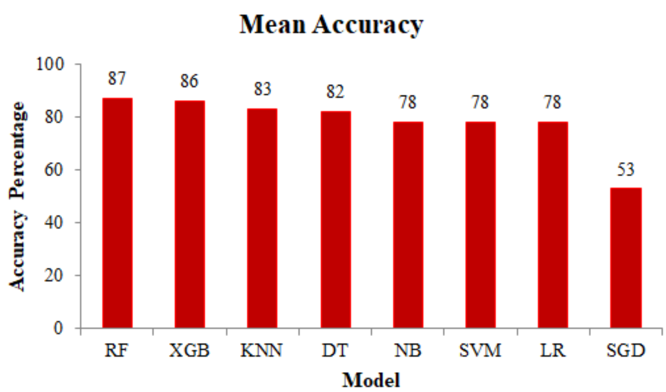


Figure 6. Comparison of accuracy results using various ML techniques

5.4. Model comparison results

Correlation is shown in Figure 7, which shows the relationship between features. The heat map is a traditional and powerful plot method to observe all the features. As Figure 8 shows, the classification method, which combines XGBoost and RF algorithms, provides excellent results compare to another model. Based on these simulations, three performance metrics can be used to determine fall detection, such as accuracy, sensitivity, and specificity. According to Figure 8, RF has the best result of training accuracy of 87%. Following this, XGBoost results achieved an 86% accuracy value. RF also has an excellent result of test specificity of 90% and a test sensitivity of 85%, respectively.

The aim of this study was to collect a fall dataset, preprocessed it as needed, and then used the data to perform findings to improve the understanding of the dataset. Our next step was to apply eight machine learning algorithms, namely, XGB, LR, RF, SGD, KNN, SVM, DT, and NB, and evaluate their performance on the following factors: accuracy, sensitivity, specificity, and precision. All the algorithms that were applied performed well with the best performance being shown by XGB and RF, indicating that these algorithms are the most efficient when it comes to predicting early fall, indicating that they are the most accurate.

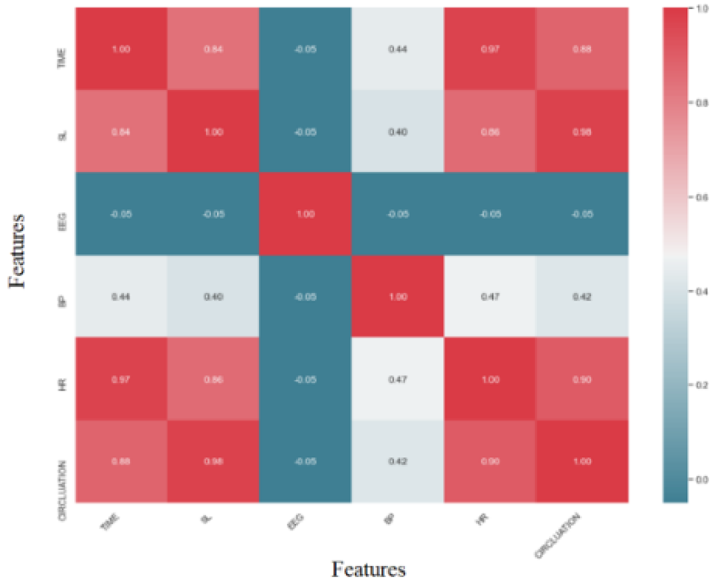


Figure 7. Correlation between features

The results of this study showed that there are features for fall detection that are highly predictive, which could be useful for clinicians trying to predict the probability of fall occurrence in their patients. This dataset did not provide enough data on the incidence of falls to adequately address all issues that might arise when using this dataset; therefore, more data and analysis must be conducted in order to produce a robust approach to predicting falls from this dataset. The limitation of this methodology will, however, require further research in the future, so that we can better understand the limitations of this method and, using machine learning approaches, we will be able to make highly accurate predictions regarding fall detection and related conditions in the future.

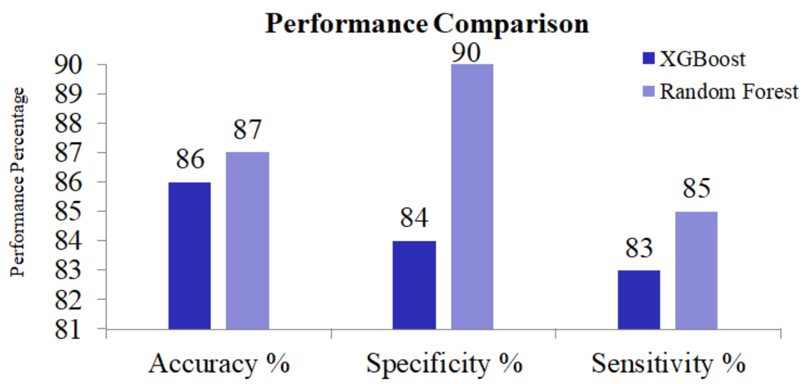
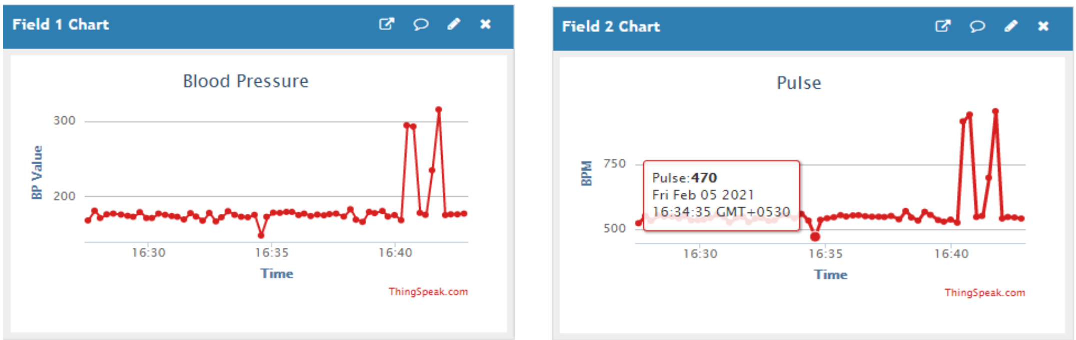


Figure 8. Performance comparison for RF and XGBoost

5.5. ThingSpeak IoT output results

According to the second approach, the real-time data from the patients is extracted using a wearable sensor. The graphical output of the BP and HR values and the procedure to update the ThingSpeak cloud storage are shown in Figures 9(a) and (b) respectively. The reliable output provided by the ThingSpeak website requires a username and password. In every data point, there is a date and time associated with it, which indicates when the data was added. From the Figures 9(a) and (b), It gives us a clear idea of the data flow transmission whenever new data is received, we are able to understand it easily.



(a) (b)

Figure 9. Data transmission chart for: (a) BP and (b) HR

6. CONCLUSION

The IoT-based fall-detection system enables to monitor of human beings health conditions continuously. In this work, health condition prediction is carried out through parameters such as blood pressure and pulse rate. Patients with an abnormal heart rate are altered, and thus, they avail of precautionary methods. The system is made more flexible; as a result, even elderly people whose ages are above 60 are more benefit. RF Classifier and XGBoost produced the most balanced results regarding the accuracy, specificity and sensitivity out of other models for early fall detection. There is a huge scope for IoT-based health monitoring; consequently, there are plenty of conceivable outcomes and enhancements in this research study.

As a way to future work, two alternate perspectives view on future work from this research is proposed, specifically data processing and security. Health-related data is collected in this study. In light of this, it is crucial to ensure that this data is transferred in a highly secure and personal manner. The various security and privacy-related methods may be implemented using standard and advanced machine learning methods. This work focused mainly on two parameters for analysis, but more parameters are there to consider obtaining perfect results. In the feature, a deep learning-based feature engineering concept is anticipated to provide a better result.

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