Machine learning classifiers for fall detection leveraging LoRa communication network

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ABSTRACT

Today, health monitoring relies heavily on technological advancements. This study proposes a low-power wide-area network (LPWAN) based, multinodal health monitoring system to monitor vital physiological data. The suggested system consists of two nodes, an indoor node, and an outdoor node, and the nodes communicate via long range (LoRa) transceivers. Outdoor nodes use an MPU6050 module, heart rate, oxygen pulse, temperature, and skin resistance sensors and transmit sensed values to the indoor node. We transferred the data received by the master node to the cloud using the Adafruit cloud service. The system can operate with a coverage of 4.5 km, where the optimal distance between outdoor sensor nodes and the indoor master node is 4 km. To further predict fall detection, various machine learning classification techniques have been applied. Upon comparing various classifier techniques, the decision tree method achieved an accuracy of 0.99864 with a training and testing ratio of 70:30. By developing accurate prediction models, we can identify high-risk individuals and implement preventative measures to reduce the likelihood of a fall occurring. Remote monitoring of the health and physical status of elderly people has proven to be the most beneficial application of this technology.

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1. INTRODUCTION

In today's world, technological advancements have become indispensable in the field of human health monitoring. With the advancement of data mining and artificial intelligence technologies integrated with systems monitoring human posture and other physiological parameters, it is significantly easier to determine how people's habits and activities impact their health and longevity [1]. Hospitals and doctors play an essential part in conventional health monitoring, but this approach necessitates significant time commitments for patient preparation, appointment making, patient waiting, doctor consultation and checkup.

Due to the difficulties of contacting professional specialists in person, adopting low-cost internet of things (IoT) technologies for patient health monitoring is essential [2]. Smart cities emphasize more innovative living and transportation and structured and intelligent health monitoring systems. On the other hand, supervising the daily activities of some particular populations, such as youngsters and the elderly, ensures that they get daily exercise. Using wearable sensors as an early diagnostic tool, noninvasively assessing vital parameters such as respiration rate, body temperature, and blood oxygen level tool, noninvasively assessing offers considerable promise [3]. Health and fitness status tracking of people has been one area in which this kind of technology has proved to be very beneficial. Miniaturized, unobtrusive, and ubiquitous gadgets are used to communicate and change their behavior according to the preferences of the user [4]. The IoT concept, which clearly refers to devices permanently connected to communication networks, has transformed how we use different technology, allowing for a wide variety of applications that rely on elements like a population's economic condition and digital abilities [5]. With the development of IoT technology, it's now possible to connect all kinds of devices, like WiFi networks, smartphones, and sensors connected, to a mobile network (3G, 4G, and eventually 5G). It paves the way for communication between these numerous gadgets and the development of collaborative smart systems that enhance the living conditions of its users [6]. However, many communities and people residing in remote areas, small towns, or single-family homes without access to extended family or consistent institutional support, especially the elderly, cannot benefit from this technological advancement [7]. Recent studies have demonstrated that the global population at risk of developing or suffering from mental disorders is expanding tremendously.

Moreover, the epidemic that has broken in the last couple of years has thrown challenges to the health sector. The United States centers for disease control and prevention (US CDC) report that 14% of confirmed SARS-CoV-2 cases required hospitalization. The sheer volume of seriously ill patients has strained healthcare facilities, resulting in delays in patient care, and compromised efficiency. The US CDC reported that 14% of SARS-CoV-2 patients required hospitalization [8]. So, it is vital to connect and use various communication and information technologies to mitigate the negative effects of these illnesses on public health [9], [10]. In the previous decade, substantial advancements have been accomplished in building wearable sensors for physiological and environmental monitoring and biochemical indicators. Wearable technology makes physiological monitoring more comfortable and affordable for consumers and healthcare professionals [11]. Intelligent sensor technologies that monitor necessary biophysical signals in real-time and let healthcare staff remotely monitor and manage health which can reduce morbidity and mortality.

To satisfy these objectives, this research offers a long range (LoRa)-based, multisensory-based health monitoring system. LoRa low-power wide-area network (LPWAN) technology extends signal transmission range and reduces battery usage. In urban areas, the theoretical coverage of LoRa is 5 km, whereas in suburban areas, it is 15 km. Therefore, a single LoRa gateway is sufficient for an entity, such as a scientific research center, school, or any organization, to deploy a LoRa system. As systems for managing and monitoring people's data advance, we seek to improve their quality of life, particularly for seniors with modest incomes. In the present study, we proposed a method using LoRa networks and cloud services.

2. RELATED WORK

In recent years, several investigations have been conducted on the usage of LoRa and low-power consumption networks. There are several potential applications of the IoT have emerged, focusing on rural development and the agricultural industry. In recent years, LoRa networks and other comparable technologies like LTE-M [12], NB-IoT [13], TV whitespace [14], and SigFox [15] have been used to construct low-power, LoRa networks for health monitoring, home automation, and agricultural applications. Also, the LPWAN technology group, especially LoRa wide area network (LoRaWAN), permits long-distance communication. LoRa communication technology connects thousands of battery-powered devices over great distances while consuming minimal power, even under bad situations, with 7 km in urban areas and 15 km in open space [16]. In addition, devices designed for prolonged battery operation must have a low power consumption. LoRa technology uses unlicensed frequencies: 433 MHz in Asia, 915 MHz in North America, and 868 MHz in Europe [17].

Modern IoT technologies use mesh network architecture which increases the communication range. But the additional responsibility of nodes to transfer messages to other nodes significantly affects the device's battery life. LoRaWAN employs star topology to boost the battery life for LoRa communication. LoRa network elements are nodes or endpoints, gateways, and network servers. Specifically, LoRa endpoints are the sensors or applications that perform the sensing and controlling. These hubs are generally located remotely. In LoRaWAN, nodes are associated with a specific gateway and transmit the received signal to a cloud-based server. Cloud-stored data are later made available through interface platforms that contain dashboards. These dashboards enable data availability and interaction on other platforms utilizing message queuing telemetry transport (MQTT) and REST web services [18]. González *et al.* [19] presented a tailored health monitoring system that monitors heart rate, temperature, and ambient characteristics, including gas level, through sensors, and transmits data wirelessly. It alerts the healthcare experts and the attendees. Health specialists will analyze the information. They collect and make decisions remotely without ever meeting with the patients themselves.

Mirjalali *et al.* [20] compiled a study of the most recent peripheral sensor devices that can accurately assess vital signs at the point of care. This review focused on different materials, designs, and mechanisms of wearable sensors for evaluating body temperature, respiratory behavior, and blood oxygen level to diagnose and monitor Covid-19. In work [21], the researchers provide an IoT-based physiological data monitoring from commercially available smart bands construction workers wear. This built platform is intended for use by construction workers in hot environments. The proposed system helps authorized individuals observe a construction worker's status remotely using a computer or smartphone. Knowledge of a patient's breathing rhythm can aid in diagnosing a vast range of medical disorders. The authors of [22] proposed a cost-effective system for classifying a patient's breathing pattern. The identification and extraction of respiratory signals from IRT and RGB films were matched to respiratory belt sensors, and the results demonstrated the viability of contactless technologies for undertaking a comprehensive breathing pattern evaluation. Another author proved the viability of monitoring LoRaWAN based wind farms and demonstrated that implementing LoRa networks permit good communication across long distances [23]. LoRa access points and edge gateways are proposed as part of Yu *et al.* [24] proposed architecture for a fall detection system (fog layer). In their implementation, bluetooth low energy (BLE) transmits health and relevant information to a LoRa gateway, which is condensed before being transmitted on a recurrent neural network (RNN) and distributed storage system. However, the authors examined only the accuracy of the proposed RNN and did not evaluate the performance of the edge and fog. Tuli *et al.* [25] introduced FogBus, a framework, to demonstrate a cost-effective sleep apnea patient prototype. Both fog computing and blockchain are included in the framework. Wireless protocols such as Zigbee, Bluetooth, and NFC link these fog nodes to the sensing layer. In work [26]–[29] implemented a real-time healthcare system model where the system architecture integrates the LoRa communication protocol, blockchain technologies, and fog/edge computing and performed runtime, cost, and power consumption analysis to evaluate the system.

3. PROPOSED METHOD

3.1. Problem statement

Low-energy-consumption, and high-precision portable sensors, have been employed in numerous investigations on patients with disorders [30], [31]. Many authors have worked on portable sensors, demonstrating the benefits of these devices in monitoring and tracking individuals. Different sensors, such as accelerometers, gyroscopes, and global positioning systems (GPS), are included in today's mobile communication devices or smartphones. But these devices are challenging to operate by people in remote places with poor network connections; as a result, we suggest exploring and improving the usage of these devices embedded with sensors by incorporating them into a system to monitor people's health condition both inside and outside the home.

3.2. Framework overview

In the present work, we proposed a structural health monitoring system with Arduino mega integrated with various sensors for fall detection, pulse oxygen, heartbeat monitoring, body resistance, and temperature. This system with health monitoring sensors serves as a remote node. The sensed values from these sensors will give vital information about health parameters. Figure 1 shows the proposed structural health monitoring architecture. The integrative framework of the system consists of several steps of implementation. The first stage entails the identification of strategic locations for creating gateways, which allows evaluation of the service quality and the usage aspects of the system. The project's subsequent phase is to prototype the functional devices of the system. In further stages, the cloud data is classified, and predictive models have been developed to identify the health risk of the people.

3.3. Machine learning classification models

Classification algorithms in machine learning use input training data to predict the likelihood or probability that the following data will fall into one of the pre-defined categories. The decision tree algorithm is one of the data mining methods that has seen the most widespread use across many industries. It is also one of the most often utilized methods. The main algorithm of the decision tree is essentially greedy [32]. Starting with the root node, each non-leaf node has an attribute in the training sample set that is put to the test. Based on the results of the tests, the training sample set is then partitioned into a large number of subsamples. Each subsample set acts as a new tree structure in this process, and the approach described above is repeated for each succeeding tree structure [33]. This is done to ensure that the loop continues to achieve the desired optimum solution.

A classification technique called random forest (RF) uses many decision trees from the input information, averaging the trees' performance to increase accuracy. Also, boosting is a sequential approach. It will apply weights to each individual tree's data. Next, it provides inaccurate classifications for the first decision tree a greater weight and inputs them into the subsequent tree. Gradient boosting combines weak learners to develop an effective learner. It successively trains models by reducing the loss function using gradient descent to increase algorithm performance. Extreme gradient boosting (XGBoost) is a machine learning ensemble approach that combines weak learners to create a strong learner. This optimized gradient boosting approach uses tree-based models and enhanced regularization techniques to increase accuracy and performance.

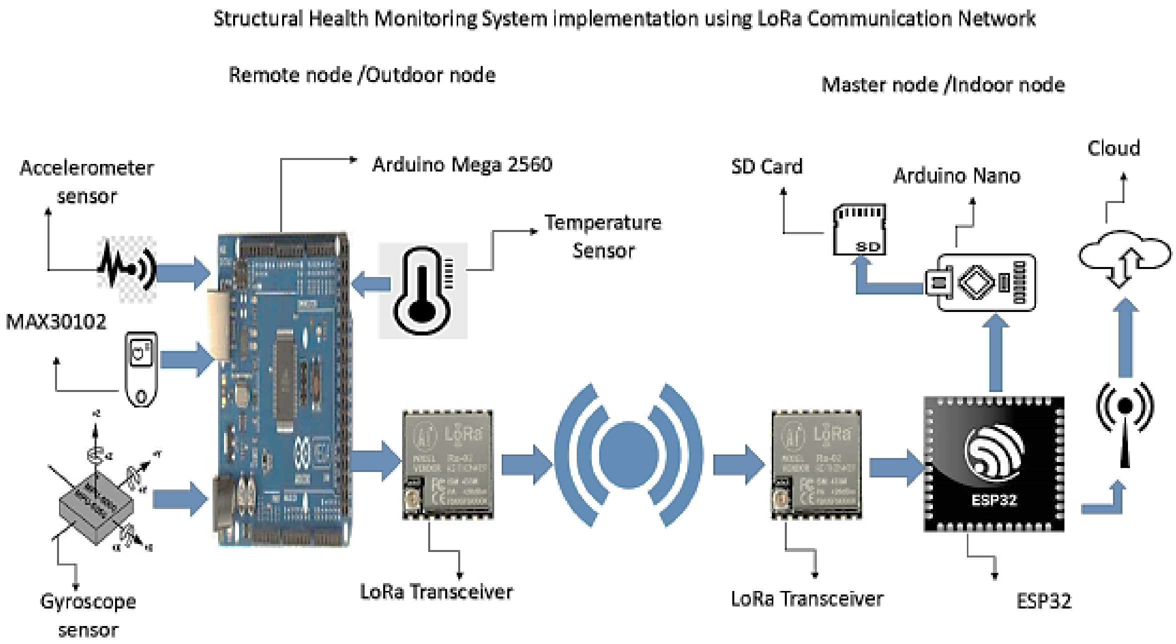

Figure 1. Health monitoring system structure using LoRa network

4. RESULTS AND DISCUSSION

4.1. Dataset

In this study, we aimed to develop a fall detection prediction model for LoRa wristband communication devices using machine learning techniques. Our dataset included information from 3,106 instances with six features. To assess how well our model works, we first created a training set of 70% of the dataset and a testing set of 30%. We applied a model and tested it using a dataset to demonstrate how machine learning approaches might be used to the given data. It is possible to develop models with increasing accuracy, significantly reducing the risk of false positives and negatives. The approach used to collect training data is consistent with the human body's normal (upright) position. Initially, the gyroscope and accelerometer sensors were calibrated, and then the gyroscope was moved in various directions to simulate human walking for all three axes of the gyroscope, maximum and minimum limit values were determined. According to the possible body positions, they are classified as "normal position," "fallen back", "fallen front", "fallen to the right", and "fallen to the left." As for the test results, the prototype's accelerometer was placed properly in a small box with a belt, and several fall scenarios were conducted on pre-defined routes. The collected data were then categorized, and the class-related column was eliminated. This allowed us to determine which data related to each group accurately.

4.2. Experimental result

In order to evaluate the model, a study of the materials and components was carried out. After that, after taking everything into account from a more practical perspective, a LoRa connection was created using LoRa transceivers. Finally, a model that can function as a LoRa node made up of various sensors and other devices as developed is shown in Figure 2. The following items make up the LoRa gateway:

- ATMEGA 2560 microcontroller IC and SX1278 (Ra-02) LoRa module, which operates on 433 MHz.
- Internet connection (WiFi/3G/4G).
- ESP32 with SX1276 LoRa 433 MHz WiFi development board with 20x4 LCD.
- MPU6050 accelerometer and gyroscope module.
- MAX30100-heart rate oxygen pulse sensor and DS18B20 temperature sensor.
- Skin resistance meter and connecting wires.

ATMEGA 2560 is a microcontroller IC microchip with a 16 MHz clock speed, with an operating voltage of 5 V. It has 54 digital I/O Pins and 16 analog input pins. One feature that makes Arduino MEGA popular among amateurs and beginners is its simple programming language. For example, Arduino MEGA is recommended if a designer has to integrate more than six analog sensors or interface a larger number of digital actuators or sensors. An experimental setup with a wristband with sensors embedded and integrated to ATMEGA 2560 is shown in Figure 2.

In the present research paper, ESP32 is a master node to collect data from various remote nodes. ESP32 is a low-power and low-cost, system-on-a-chip with embedded Bluetooth and WiFi modules, which easily be connected to the cloud. ESP32 is designed for IoT applications, wearable electronics, and mobile devices. It achieves ultra-low power consumption with the use of a blend of proprietary software. The ESP32 delivers invaluable capability and versatility to applications that require minimal printed circuit board (PCB) specifications.

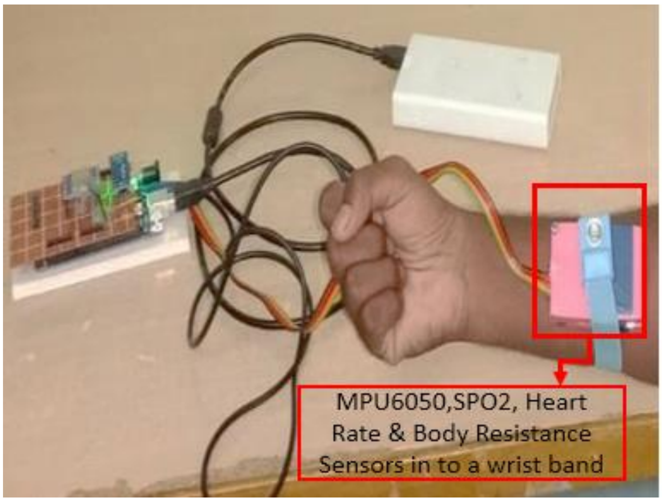

Figure 2. Experimental setup of health monitoring LoRa outdoor node

4.3. Evaluation indicators

To create a direct comparison with the classification models benchmark. The point-based detection index is often employed in sequence data; when the projected value overlaps with the actual value, it is recorded as a true positive, while the predicted value and any real value are recorded as false positives. When the values do not overlap, it is reported as a false positive. A false negative is recorded when there is no overlap between the actual and predicted values. The performance metrics [34], [35] are calculated for the fall detection problem by (1) to (4):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 = \frac{Precision\ X\ Recall}{Precision+Recall} \quad (4)$$

where TP is true positive, FP is false positive, TN is true negative, and FN is false negative.

4.4. Result analysis

The data is preprocessed, and the description of the dataset is shown in Table 1. Now we must use machine learning algorithms for classification and choose the optimal model based on recall and precision. The various classification models are compared with each other while the performance metrics are recorded. As illustrated in Figure 3, we follow the concept of classifying data from various categories to the maximum extent feasible while developing a decision tree. As a result, we employ the Gini coefficient as a loss function while constructing a classification and regression tree (CART) decision tree. From the decision tree, fall prediction first classifies the tree into normal and abnormal fall detection. Further abnormal falls are classified into fallen left/right or fallen front/back. It has been found that the generalization error will be reduced in proportion to the number of base classifiers that are present in the decision tree. The algorithm achieves an accuracy of close to 99.8634% of the time.

Table 1. Training data model framework for decision trees classification

Model framework			
Tools	: Python programming		
Scheme	: Decision trees		
Attributes	: 4		
Test mode	: Training 70%, Testing 30%		
Decision tree classifiers			
Conditions	Classification	Count	Errors
Gyroscope value≤1.003	Normal	514	
Gyroscope value>1.003	Abnormal	1658	
Gyroscope value≤or>3.051	fallen left/right		
Gyroscope value≤1.501	fallen left	220	
Gyroscope value>1.501	fallen right	688	2
Gyroscope value≤or>4.503	fallen to front/back		
Gyroscope value≤4.503	fallen front	371	
Gyroscope value>4.503	fallen back	378	1
Total		2171	3

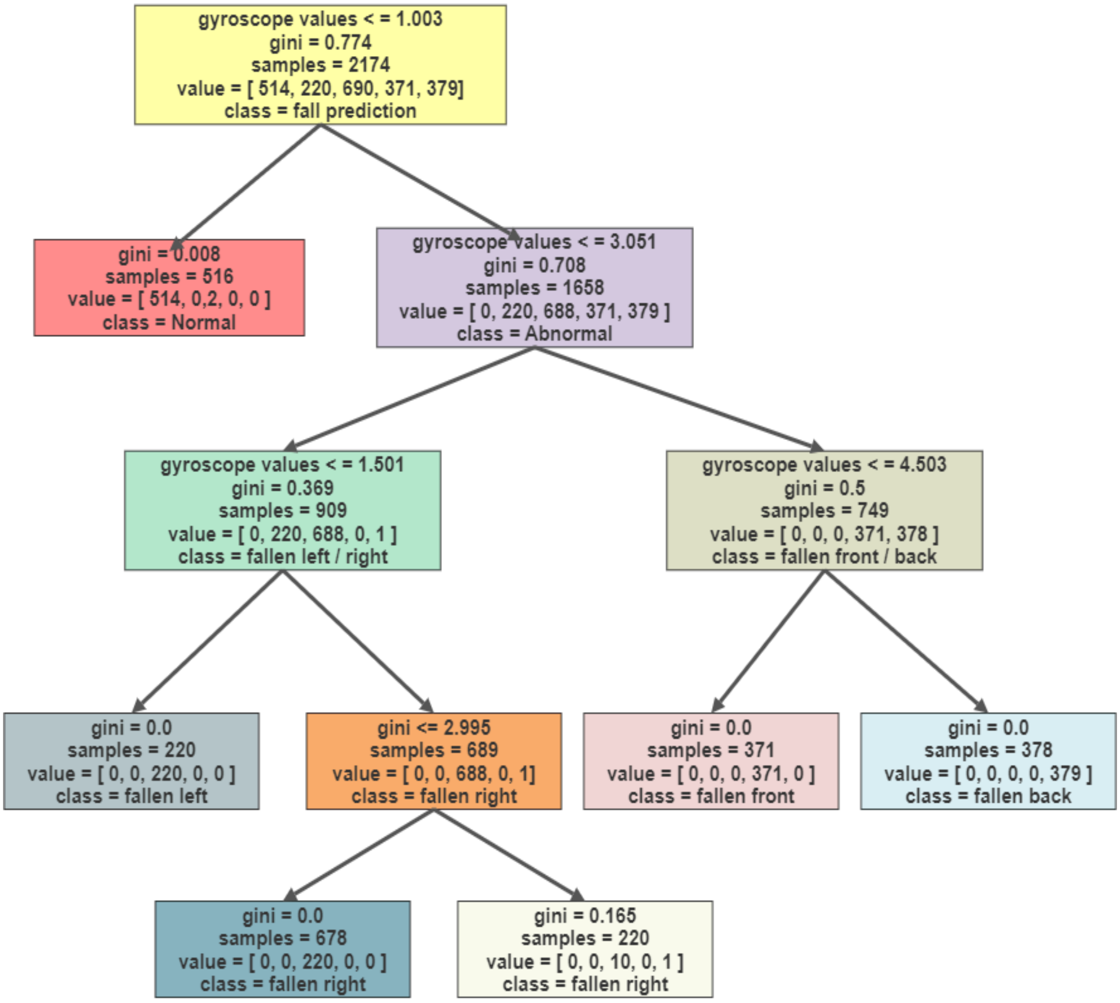

Figure 3. Decision tree classifier

When the data collection is huge, we use python programming to construct a decision tree by randomly selecting a subset of the whole dataset. By repeating the aforementioned procedure, it is possible to generate multiple decision trees with diverse nodes and shapes. These trees form a RF by joining together. With bootstrap sampling, n subsamples are first selected from the sample set. We create a decision tree for each sample subset by randomly picking K features, including normal, fallen right, fallen back, and fallen front.

To create a random forest with n CART decision trees, repeat the previous two steps n times. As illustrated in Figure 3, n decision trees' voting outcomes determine the record type.

All symbols that have been used in the equations should be defined in the following text. The confusion matrix is shown in Table 2 and according to Table 2(a), all predicted normal (upright) position occurrences were accurately identified, with just three instances classified incorrectly, which is not very noteworthy in the training dataset. As a consequence, the model is quite close to reality. After that, the decision tree model was deployed to a test groups shown in Table 2(b), yielding remarkably consistent results with just two occurrences incorrectly categorized.

Table 2. Confusion matrix for (a) training dataset and (b) testing dataset

Parameter	Normal	Fallen left	Fallen right	Fallen front	Fallen back
Normal	514	0	0	0	0
Fallen left	0	220	0	0	0
Fallen right	0	0	688	0	0
Fallen front	2	0	0	371	0
Fallen back	0	0	1	0	378

(a)

Parameter	Normal	Fallen left	Fallen right	Fallen front	Fallen back
Normal	248	0	0	0	0
Fallen left	1	83	0	0	0
Fallen right	0	0	266	0	0
Fallen front	0	0	1	169	0
Fallen back	0	0	0	0	164

(b)

Table 3 compares the degrees of accuracy achieved by each of the algorithms we have used. The various accuracy metrics are shown in the table. The accuracy measurements are presented in the comparison table in a manner that is lowering with respect to the training and test ratios. We are able to see that the decision tree achieved a good level of accuracy by obtaining 0.998634 when the ratio was 70-30. Following that is XGboost with an accuracy of 0.99862 at a 70-30 ratio, and the accuracy that is achieved by gradient boosting using the classifier technique as a basis has the lowest accuracy at 0.99785 at a 70-30 ratio. Based on the table of results, we can see that the decision tree classifier did very well in contrast to the other methods.

Table 3. Comparison of all algorithms

Model	Training dataset				Testing dataset				Train data	Test data
	Accuracy	Precision	Recall	F1 score	Accuracy	Precision	Recall	F1 score		
Decision tree	0.99863	0.99859	0.99861	0.99785	0.99785	0.99786	0.99785	0.99765	2,174	932
Random forest	0.99678	0.99465	0.99460	0.99463	0.99563	0.99462	0.99459	0.99464		
Adaptive boosting	0.99623	0.99464	0.99423	0.99565	0.99565	0.99462	0.99431	0.99468		
Gradient boosting	0.99785	0.997	0.99786	0.99785	0.99685	0.99691	0.99785	0.99778		
XGBoost	0.99862	0.99811	0.99831	0.99865	0.99864	0.96712	0.99785	0.99859		

5. CONCLUSION

This research investigates a very important societal use, taking into account the potential underlying LoRa technology, which is currently available on the market at a reasonable price. The increasing demand for designing low-cost, low-power, and LoRa IoT systems as wearable devices or remote nodes has great potential for monitoring elderly people and their residences. We analyze and forecast fall detection properties using different classifier algorithms. To further investigate the efficacy of fall detection utilizing the LoRa communication network, a CART model has been constructed using an enhanced decision tree algorithm. All reliable data classifiers employ optimum splitting settings and advanced tree pruning methods to increase accuracy. By comparing the outcomes of the decision tree CART, RF, adaptive boosting, gradient boosting, and XGBoost algorithms, as well as by constructing a decision tree algorithm based on the CART classifier, it was found that a decision tree algorithm with a different number of classifiers improved the classification evaluation indexes. As a result, the true rate, precision-P, recall-R, and F1 values were all increased, and the decision tree method achieved an accuracy of 0.99864. The precision of the classification has now been achieved at its optimal efficiency.

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