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ACCIDENT ATTENTION SYSTEM FOR SOMNAMBULISM PATIENTS: IOMT BASED SMART HEALTH CARE SYSTEM

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Abstract. Promising technologies such as sensors, networking, and edge have led to many smart healthcare solutions to monitor and track patient health status. The health sector is now experiencing a significant transformation from conventional patient care to a smart healthcare environment. Smart health care allows medical professionals to monitor patients remotely and visualize the disease prognosis effectively. The Internet of medical things connect patients, doctors, and medical equipment via wireless networking technologies to process the data with Artificial Intelligence models. One of the domains of automated health care systems is to alert the caregivers and hospital on emergency conditions. This research study is a novel work that aims to help the caregivers of somnambulism patients attend to them in case of emergency. Sleep quality improves the health and work efficiency of any person. The caregivers of sleepwalking patients suffer from lack of sleep as the patient gets active during the night hours. The model is based on fall detection and sleep detection from wearable sensor data. The fall detection model includes feature selection by LASSO and classification by ensemble classifier. The proposed methodology shows improved performance for the fall detection model for all ensemble machine learning classifiers.

Key words: Internet of Medical Things, Somnambulism, Fall detection, LASSO, Ada Boost, Random Forest, Gradient Boosting.

1. Introduction. Somnambulism or Sleepwalking is a common disorder among children and adults. Somnambulism patients in the early hours of the night tend to walk in their sleep. Somnambulism is a disassociated consciousness where the patient is partially asleep and partially awake [1]. Children suffering from sleepwalking outgrow it in puberty, but some suffer from it even in adulthood. Sleepwalking is triggered by stress, anxiety, medications like sedatives, or sleep-disrupting noise or touch. The patients who sleepwalk end up doing dangerous acts in their sleep. Their eyes remain fully or half open, and they are not fully conscious of their activities. They see through the person standing beside them. They do not respond to the presence of individuals near them while sleepwalking. When a conversation is made, they may partially respond to the conversations made to them or tend to blabber. There is always a danger of tripping over things and getting injured [2]. Sleep quality is measured by sleep latency, total sleep time, duration of nocturnal awakenings, rapid eye movement (REM) state, and non-rapid eye (NREM) movement state [3]. Sleepwalking in patients occurs when there is a transition from deep NREM sleep before the REM sleep stage [4]. After the sleepwalking episode, the patient returns to a sleep state and has amnesia about the sleepwalking episode after waking up [5]. Parents must be vigilant every night as Sleepwalking is a regular issue. Parents suffer from anxiety, and their sleep is disturbed by the child's activities in the nighttime. Irregular sleep patterns affect physical and mental health issues. Sleeplessness leads to depression and obesity. Good sleep helps a person maintain a healthy weight, reduce stress, and to improve mood [6]. When the child sleepwalks, the parent must gently guide them back to bed. A smart healthcare monitoring system alerts the caregiver if the patient sleepwalks and wakes the caregiver to guide the patient back to bed. The caregiver or parent can relax at night as they are confident that the smart healthcare system will alert them in case of an emergency or sleepwalking episode. The advent of the Internet of Medical Things (IoMT) with sensors, artificial intelligence systems, machine learning algorithms,

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and ubiquitous computing promises smart healthcare solutions for monitoring patients who require continuous monitoring and care [7]. Smart health care is an intelligent system that transforms traditional medical methods into more convenient, effective, personalized ones. Smart healthcare concept originates from smart planet. The smart planet integrates sensors that record and transmit data to cloud servers via networking. The Artificial Intelligence model for diagnosis processes the transmitted data. Smart health care leverages this technology to monitor patients and detect abnormal health conditions via health parameters. Smart health care aims to alert caregivers and doctors in an emergency. Besides emergency care, smart healthcare systems diagnose the disease, aid decision-making, and maintain patient records. [8]. This research study aims to develop a smart healthcare system that will alert the caregiver in case of any sleepwalking episodes or fall episodes during the sleepwalk. On receiving a sleepwalking alert from the patient, the caregiver can attend to the patient immediately and, in case of fall episodes, provide emergency help. This research work is novel as no smart healthcare IoMT models were implemented to alert caregivers about the patient's sleepwalking episode to our knowledge. Sleepwalking does not result in severe trauma or injuries, but it can aid caregivers, especially parents, to have quality sleep. This smart healthcare system will free them from the anxiety of sleepwalking episodes of their loved ones.

2. Literature survey. Sleep is an essential factor for leading a quality life. Several AI-driven IoT healthcare models were developed to detect sleep disorders. This IoMT model that alerts the caregivers of Somnambulism or sleepwalking patients is a novel work by the authors. Sleepwalking patients do not have fatal or severe injuries during the fall episode. Hence an IoT healthcare system for sleepwalking disorder still not considered for implementation by researchers. This research focuses more on the parents or caregivers under continuous stress in the night hours living with patients suffering from sleepwalking. An IoMT-based health care system allows caregivers to get a relaxed sleep as they are sure to be alerted in an emergency. There are few IoMT models for Somnambulism monitoring, so this section discusses the basic IoMT model for monitoring sleep disorders. Obstructive Sleep Apnea (OSA) is a sleep-related breathing disorder. OSA is one of the sleep disorders that cause cardiovascular and cerebrovascular disease. OSA can be remotely diagnosed by the IoMT system from physiological signals of human sleep. Short-term heart rate variability (HRV) signals extracted from ECG signals detect sleep apnea in patients [9]. OSA is detected with SpO_2 sensor estimating the heart rate and blood oxygen levels. This data is presented to the patient via mobile phones and personal computers [10]. Sleep Apnea is detected by a heart rate variation sensor, finger oximeter SpO_2 sensor, ECG sensor, Galvanic skin response (GSR) sensor, and sound sensor to monitor the snoring sound in patients. Arduino processes the sensor data. Sleep Apnea causes lower heart rate due to lack of oxygen. ECG can record unusual patterns in the heartbeat during sleep. The blood oxygen level is a measure of oxygen distribution in the body. During OSA, the breathing rate falls. Sleep Apnea has SpO_2 value of 90 percent compared to 95 percent in healthy person. This leads to Hypoxemia, a chronic lung disorder. The model detects sleep Apnea in patients with sensors, Arduino, and Bluetooth modules [11]. According to WHO, good sleep quality is essential for a healthy person. Irregular sleep patterns affect a person's mental health causing depression. IoT models monitor the sleep quality of patients by measuring the body movement, SpO_2 rate, heartbeat, and snoring pattern. Sleep quality monitoring can provide better treatment for sleep disorders [12]. The study proposes IoT-enabled sleep data fusion networks to monitor and analyze patient sleep data. The data fusion-enabled multi modal sleep-data analysis system analyses the sleep data. The machine learning model detects snoring and coughing. The system records the patient's audio while sleeping and detects coughing, snoring, and sleep-talking [13]. The IoMT system is developed to classify the various vocal fold disorders by acoustic speech signal processing [14]. Sleepwalking patients are monitored and protected by a model that can detect a person falling or trying to go out of doors or windows unconsciously during sleepwalking [15].

3. Background.

3.1. Architecture of IoMT. Internet of Medical Things (IoMT) is a network of sensors, devices, artificial intelligence algorithms, and mobile computing technology that automates health care. IoMT monitors chronic patients remotely, tracks patient medication orders, maintains patient medical details, tracks patient's locations, and facilitates emergency help. IoMT reduces medical management costs and improves data sharing among the entities of IoMT. IoMT consists of four layers: the sensor, gateway, cloud, and visualization layers [16]. The lowest layer is the physical layer that consists of sensors for recording health care parameters from the patients.

The data from wearable devices, sensors, and other medical equipment are collected in the data acquisition layer of the perceptual layer and transferred to the network layer via data transfer technologies. Technology like Bluetooth, ZigBee, and Wi-Fi aid in short-range data transfer [17].

3.1.1. Perception Layer. Wearable devices have sensors that can continuously measure the patient's health parameters without any failure. This feature has enabled the emergence of smart healthcare systems that constantly monitor the patient's health condition and alert on emergencies. The wearable sensors measure the patient's continuous glucose level, pulse, heart rate variability, skin temperature, body temperature, sweat release, body posture, and blood oxygen level [18]. This valuable information may be maintained for perusal by medical practitioners for future treatments. These wearable sensors, medical devices, and actuators have enabled healthcare systems to perform flawlessly and efficiently. This is the reason for the success of IoMT-based healthcare models. In IoMT architecture, the wireless network transmits the data from the data access layer to the processing layer. The layer integrates the mobile communication network, wireless sensor network, and internet technologies [19]. The processing layer includes the edge, fog, and cloud layers that generate meaningful information from the data collected by physical devices. Edge computing ensures data privacy, a significant factor while transmitting confidential patient data over a wireless network. Edge presents low latency as they are closer to the physical device and require low bandwidth. Edge computing is preferred in IoMT as the model demands immediate real-time decision-making for time-sensitive applications. The advantages of edge computing are pre-processing the data before moving to the cloud and establishing a secure bidirectional data transfer between the cloud and lower layers. Edge supports various medical devices, communication technologies, and protocols [20].

3.1.2. Processing Layer. The fog layer is a distributed decentralized infrastructure that processes extensive data in the fog layer without transferring it to the centralized Cloud. Fog computing overcomes the disadvantages of Cloud computing and enables data processing closer to the device edge. The advantages of fog computing are reduced computational cost and memory usage. The data transmission time is reduced by increasing the fog nodes and adopting effective edge-mining techniques [21]. Fog cannot replace the Cloud layer but will be an added layer in data processing in an IoT environment. However, it adds additional expense due to extra devices. Edge computing allows computing to be performed closer to the network's edge. Edge network reduces latency and boosts the network speed. Data is processed and stored in localized devices. Edge requires less bandwidth at the data center level as the data are stored and processed in localized servers. Latency and low bandwidth lead to less cost. Security is an essential issue with edge computing as the data is localized, and the probability of hacking and tampering is higher. Due to hardware damage, edge computing risks losing data when stored in the hardware layer. Fog is an intermediate layer between the Cloud and the edge layer. The edge layer transmits the sensor data to the fog layer over a localized network. Streaming large files from the edge layer to the cloud layer continuously results in high latency. Streaming the files to the fog layer and processing it in the fog layer reduces latency. The system under study is a patient monitoring system where edge computing can be a suitable option compared to fog computing.

Cloud has data storage and computation resources for data analysis, visualization, prediction, and classification. Cloud processes data stored in data centers with long-term deep analysis techniques that induce high latency, a vital factor for real-time monitoring. The cloud layer above the fog layer allows extensive data stored and processed by cloud servers far away from the client devices. In the IoMT edge, the fog and cloud layers are integrated into a single layer for data processing. This layer ensures quick response time, a significant factor in monitoring systems. The cloud layer leverages machine learning and deep learning algorithms to classify and predict the data stored in the data centers to monitor the patient under care. Artificial Intelligence models in IoMT provide real-time solutions for treatments based on historical and current patient data. The AI models in the Cloud layer can make disease diagnoses, schedule appointments, medications, and disease stage predictions [22]. The Security of patient data is one of the challenges faced by data storage in the Cloud.

3.1.3. Application Layer. The goal of developing health care systems is to monitor patient status, track health status, create emergency alerts, schedule appointments for the patients, and track treatment prognosis. The applications are used by medical health practitioners, patients, and vendors. Applications can reside in the physical layer close to the sensors, some in the edge layer performing real-time processing and others in the

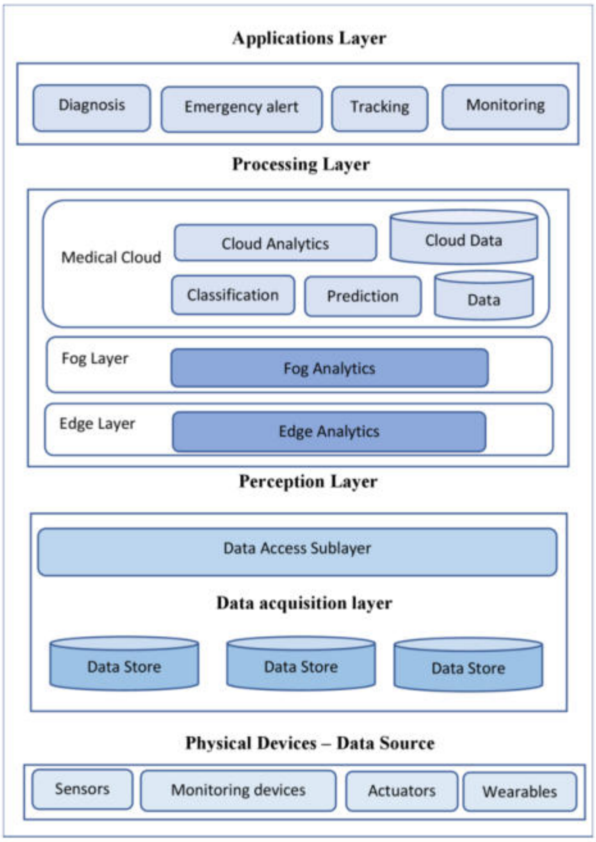


Fig. 3.1: Architecture of IoMT

cloud or application layer. Applications monitor vital health parameters, mental health monitoring, glucose monitoring, posture monitoring, and cardiovascular monitoring in patients. Health applications are developed to alert caregivers of patients who have Alzheimer's disease [23], Epilepsy[24], and stroke. Applications can be developed for normal fitness care and m-health. Figure 3.1 shows the fog-based architecture of the IoMT model.

3.1.4. Infrastructure. The proposed model requires wearable devices with medical sensors, customized applications designed to alert the caregiver, smart phones, desktop computers, and an uninterrupted internet connection. The recommended minimum speed of internet connection speed is 100 Mbps. The sensor needed for this proposed system includes the APDM Opal IMU sensor and the Apple watch sensor photoplethysmography. The APDM opal sensor measures the patient's spatial or temporal gait and balance parameters. AWS edge services ensure data processing, analysis, and storage in the edge layer. The service allows deploying APIs and tools to locations outside the AWS data centers. IoT edge services like FreeRTOS from AWS help in programming, deploying, managing, and securing the low-power edge devices.

3.2. Proposed System for Accident Attention System in Somnambulism Patients. This study proposes an accident attention system for patients suffering from Somnambulism. The patients suffer from sleepwalking when aroused from the deep non-rapid eye movement (NREM) sleep stage. Sleepwalking patients

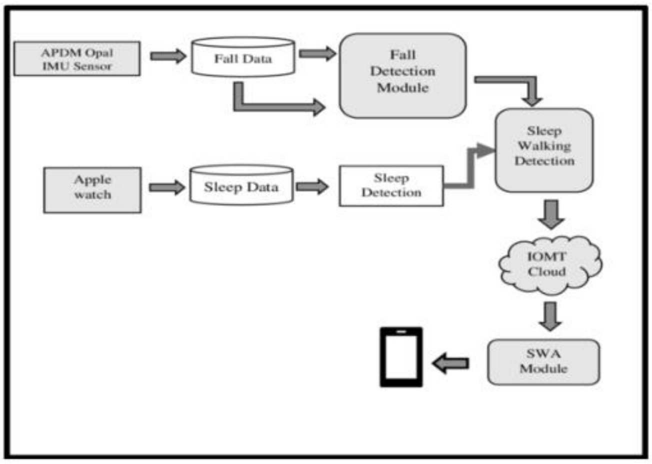


Fig. 3.2: Proposed System for Accident Attention System for Somnambulism Patients

are at risk of falling from heights. There is a chance of falling from balconies or stairs while sleepwalking inside the house. Caregivers of sleepwalkers should maintain a diary to record the timings of such episodes. The caregivers should predict the time of sleepwalking and wake up at least 15 minutes before such attacks [25]. This proposed accident attention system alerts the caregiver or parent when the patient starts sleepwalking.

Figure 3.2 represents the methodology for accident attention system for Somnambulism patients.

3.2.1. Dataset. The Opal wearable sensor has an accelerometer, gyroscope, and magnetometer. The wearable APDM opal IMU sensor records data at 128 Hz at seven body locations. The locations where body movement measurements are recorded include the right ankle, left ankle, right thigh, left thigh, head, sternum, and waist. The Inertial Measurement Unit Fall Detection Dataset is the labeled dataset with APDM Opal sensor data recordings to record the fall and daily activity. The dataset for sleep detection is the data with acceleration (in units of g) and heart rate (bpm) measured from Apple watch sensor photoplethysmography and sleep data from polysomnography. Data were collected at the University of Michigan from June 2017 to March 2019, with 31 subjects [26]. The dataset includes x, y, and z acceleration motion details, heart rate, steps, and labeled sleep. The sleep table has a subject id and -labeled class data. The class includes stages of sleep such as a wake, N1, N2, N3, and REM. Wake is labeled as 1, N1 as 2, N2 as 3, N3 as 4, and REM as 5.

3.2.2. Feature Selection. The proposed methodology in this study records data from the APDM Opal IMU sensor for fall detection and records the sleep status from the Apple Smart Watch. The proposed AI model, SWD, is trained with IMU dataset by a machine learning algorithm and classifies the test data as FALL or ADL. If the SWD module detects the fall, the SWA alert system alerts the caregiver of the fall or ADL episode. The SWD module also makes decisions based on the sleep data recorded by the Apple smartwatch. If the patient is sleepy and falls while sleepwalking, it alerts the parent or the caregiver. The mobile application is designed to alert the patient's caregiver with a notification. The proposed fall detection module detects falls and daily activity with the sensor data. The dataset is a high-dimension dataset; hence, a feature selection process will identify the most significant features in the dataset. Feature selection is a preprocessing step in the model before classification that improves the performance of the classification model. The IoMT architecture must be designed to provide quick response for emergency alert systems hence feature selection prior to classification will reduce computation time significantly. The selected features and the data samples are the input to the classifier. This improves the model's performance. The classifier model performance reduces with redundant and non-deterministic features [27]. The features in the dataset should be strongly correlated with the response variable. The features with weak correlation with the response variable can be eliminated from the dataset [28].

The classifier performance after feature selection is experimentally studied in Python language. The feature selection method adopted in this study is LASSO feature selection method. LASSO is the least absolute shrinkage and selection operator initially formulated by the researcher Tibshirani (1996). LASSO performs two primary and important tasks of regularization and feature selection. In Lasso feature selection method, an upper bound is given to the absolute values of model parameters. The coefficients of the feature variable are reduced to zero to identify the best deterministic features. After shrinking the operator, the features with nonzero coefficients possess high discriminating power [29].The feature vector constructed in this study is a multiple feature model which is expressed as

$$R_i = \beta_0 + f_1\beta_1 + f_2\beta_2 + ... + f_j\beta_j + \epsilon$$

where feature variable set is $f_1, f_2, ...f_j$, and coefficients are $\beta_1, \beta_2, ...\beta_j$ and ϵ is error. The linear regression model tries to predict the value of the response variable for the given sample of feature variables by reducing the sum of square residuals and generating a perfect fit for all the data samples available in the data set. The lasso solves the l_1 optimization problem by minimizing the function

$$\Sigma_{i=1}^{n}(R_i - \Sigma_j F_{ij}\beta_j)^2 + \lambda\Sigma j|\beta_j| < t$$

where t is the upper bound and λ is the tuning parameter. The higher the value of higher the number of coefficients shrinking to zero. When the upper bound reduces to zero all coefficients also reduce to zero. The features with non-zero coefficients are included in the reduced dataset.

3.2.3. Classification. The classification model in this study was carefully chosen after the experimental study of the performance of classifiers with Python. The classifiers like Random Forest, AdaBoost, Logistic Regression, Naïve Bayes, and K-nearest neighborhood (kNN) classifier were experimentally studied for performance evaluation. The Random Forest classifier is based on the Bagging technique. It's an ensemble classifier that uses multiple weak learners to build a robust classifier. In Random Forest algorithm, both feature and row sampling are carried out to create input datasets for the different base learners. The base learners train on different sample sets and classify a new data sample as one of the categorical classes. The final vote is based on the majority voting scheme from the results of the different base learners. Freund and Schapire proposed the Adaptive boosting (AdaBoost) algorithm [30]. The AdaBoost is based on boosting technique and Random Forest on bagging technique. In the Random Forest classifier, the base learners work in parallel, whereas in AdaBoost the base learners work in a tandem manner. AdaBoost stumps for each variable perform classification rather than trees. Stumps are weak learners, but that is the reason for the success of AdaBoost classifier.

In Random Forest, all the decision trees created have the same importance, whereas in AdaBoost some stumps have higher significance in affecting classification than others. In Random Forest, the order of the decision tree does not affect the classification performance, but in AdaBoost the order of the stumps affects the classification performance. Each sample in the dataset is assigned equal weights in the first step. Stumps are created for each feature and the number of misclassifications and correct classifications are calculated. The Gini index is calculated for the stumps. Depending on how significantly the feature performs classification, it gets a higher say in the classification. This is based on total error. The total error is the sum of the weights of incorrectly classified samples. The total error varies between 0 to 1 for the stumps. The significance of the stump depends on the total error. When the computed total error for the stump is close to zero, the stump has higher impact on the classification performance. If the total error is 0.5, then its impact on classification performance has a probability of 0.5. If the total error exceeds 0.5, the feature impact on the classifier is very low. The features that have higher classification power classify the dataset. Logistic regression is a classification algorithm that values the association of one or more independent feature variables in the dataset with the response variable. Logistic regression mathematically predicts the chances of outcome based on the feature values. The estimated probability is between 0 and 1 [31]. Suppose there is no dependency between the feature variables and response variable then the probability is low. If there is a strong dependency between variables, then the probability is high. LR in medicine is applied in areas for tracking the prognosis of patient treatment by predicting disease conditions and chances of disease affecting a patient [32].

Naïve Bayes finds its application in medical diagnosis, text classification, and sentimental analysis. Naive Bayes classifies an unknown data sample with probabilities computed while learning the data pattern in the

Table 5.1: Selected features by LASSO for IMU Dataset

Left thigh Acceleration X	Waist Acceleration Y	Waist Acceleration Z
Waist Angular Velocity X	Waist Angular Velocity Y	Waist Angular Velocity Z

Table 5.2: Performance Evaluation of Fall detection Module

Common	Precision		Recall Rate		F1 Score		**Accuracy**	**AUC**
Classifier	**ADL**	**Fall**	**ADL**	**Fall**	**ADL**	**Fall**	**of Model**	**of Model**
Random Forest	100	100	100	90	100	99	100	0.99
AdaBoost	99	99	100	99	99	99	99	0.99
Gradient Boosting	100	99	100	99	100	99	100	0.99
Logistic Regression	98	96	98	96	98	96	97	0.96
Naive Bayes	99	93	97	99	98	96	97.17	0.97
KNN	100	100	100	99	100	99	100	0.99

training data. It is named as “Naïve” due to the assumptions that the features are strongly dependent. Naïve Bayes works well with medical data though some clinical features are independent [33]. The Naïve Bayes method calculates the probability that a particular data sample belongs to one of the categorical classes in the dataset. The probability that the data sample belongs to the class is calculated, and the data sample is finally classified to the class which has maximum probability. The probability is calculated based on the train data. K-nearest neighbor is a classification algorithm where the data samples are classified as one of the classes based on the similarity of the other data samples in proximity -to the data point [34]. The data sample belongs to the class to which majority of data points belong. The k value decides the number of data samples around the test data to be selected for decision-making. K- value should be odd to avoid ties in the result decisions.

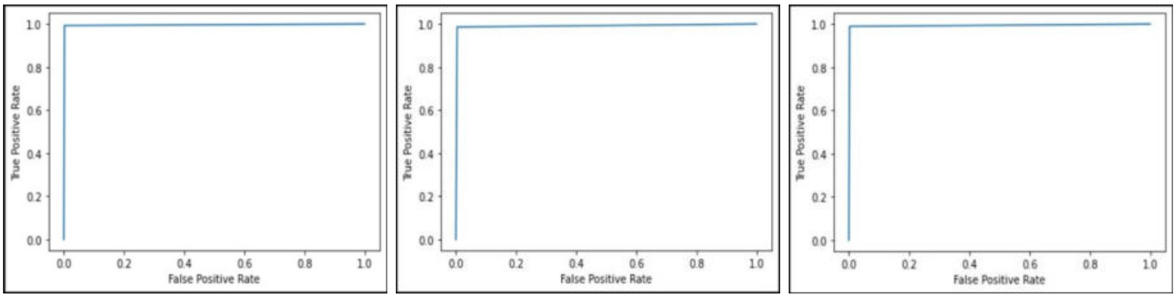
4. Performance Evaluation. The classifiers are evaluated on the accuracy, recall rate, precision, and f1-score. The area under the curve (AUC) is also recorded for each classifier. The area under the curve is the area under the Receiver Operating Curve (ROC) that represents the performance of the model. AUC value varies from 0 to 1. When AUC is close to 1, the model performance is best.

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN},\ precision = \frac{TP}{TP+FP},\ recallrate = \frac{TP}{TP+FN},\ F1 = \frac{precision * recallrate}{precision + recallrate}$$

5. Results and Discussion. The fall detection module is implemented in Python language. The dataset considered for the implementation of the Fall detection model is the IMU fall dataset The dataset is preprocessed by the LASSO feature selection method. The features identified by the LASSO method is given in Table 5.1. The classifiers Random Forest, AdaBoost, Gradient Boost, Logistic Regression, Naïve Bayes, and K-nearest neighborhood are compared for performance evaluation. The results of the experiments are recorded in Table 5.2. The reduced dataset with the selected feature is the input to the classifiers.

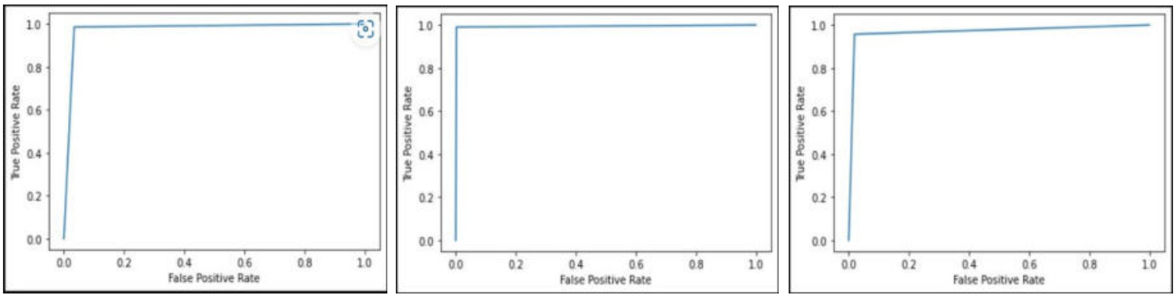
Figure 5.1 shows the ROC curves for the ensemble Classifiers. ROC maps false positives on the x-axis and true positives on the y-axis. Accuracy is the ratio of correct classifications made to the total number of classifications made. Precision is the ratio of true positives to total positive classifications made in the dataset. The recall rate is the ratio of true positives to the sum of true positives and false negatives in the dataset. F1-score is the harmonic mean of precision and recall rate [35].

Figure 5.2 shows the ROC curves for the machine learning classifiers. From the recorded results, it is evident that the ensemble method is more efficient compared to the single-base learner classifier model. The ensemble method has higher classification power than other ML algorithms as it leverages the pros of the multiple weak classifiers. The weak learners are decision trees in ensemble methods. They avoid overfitting data and give high accuracy for the model. Random forest performs well with both complete and reduced dataset as they identify the significant features in the dataset. AdaBoost performs well with such data as the model runs in sequence



(a) Random Forest Classifier (b) AdaBoost Classifier (c) Gradient Boost Classifier

Fig. 5.1: ROC for Ensemble Classifiers



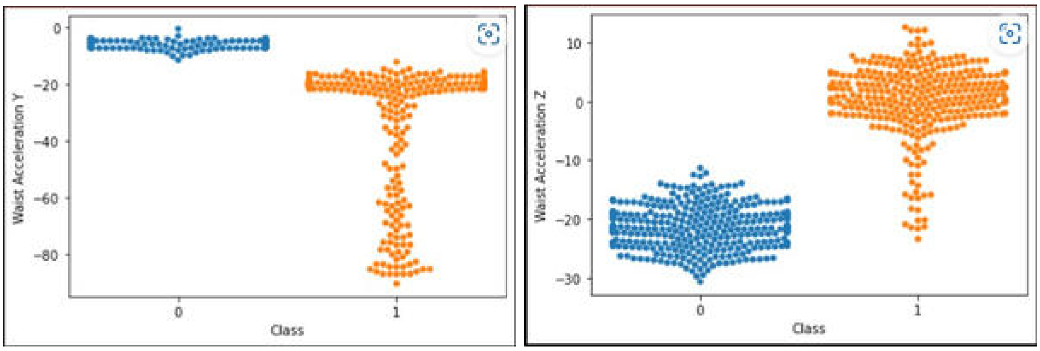
(a) Naive Bayes Classifier (b) KNN Classifier (c) LR Classifier

Fig. 5.2: ROC for Common Classifiers

and avoids overfitting. The model has weights associated with the features that give higher priority to the mis classified data samples in the consecutive models. kNN also performs well for the feature-reduced dataset as the algorithm is robust for similar class data with a prominent similarity index.

In a nutshell, the ensemble classifiers perform exceptionally well as the samples in the dataset are large, and the feature set is reduced to five, excluding the labeled class feature. Logistic regression generally performs well with large feature datasets rather than datasets with few features. Naïve Bayes works well when the dataset has categorical rather than numerical inputs. So Logistic regression and Naïve Bayes classifiers do not perform highly compared to the other classifiers. The Random Forest classifier is the most suitable machine learning classifier for the proposed system. The performance of Random Forest is best compared to the other classifiers. Random forest classifier performs well even if one class is less frequent in the dataset than the others. In the case of real-time datasets where the data samples of fall episodes are less compared to the ADL samples, the algorithm can give high accuracy to the model.

6. Data Visualization. The data visualization of such a large dataset is not feasible. Hence, 625 random data samples are selected from the dataset, and visualization is carried out with the Seaborn library. Waist acceleration Y and Waist acceleration Z are the features considered for visualization. In the figure 5, class 0 is ADL, and class 1 is Fall data. Figure 6.1(a) shows the class as the x-axis and the waist acceleration Y as the y-axis. Figure 6.1(b) shows the class as the x-axis and the waist acceleration Z as the y-axis. The visualization indicates waist acceleration Y values for ADL falls between 0 and -20. The waist acceleration Y values for FALL are negative values below -20. In Figure 5.2(b), waist acceleration Z values for ADL are in the range of 0 to -10, and for FALL, the values are more in the positive range from 0 to 10. The visualization clearly shows



(a) Class vs Waist Acceleration Y (b) Class vs Waist Acceleration Z

Fig. 6.1: Data Visualization

the demarcation of the feature values for the two different classes.

7. Conclusions. The proposed accident attention model is developed with the objective of alerting the caregiver to somnambulism when the patient starts sleep walking or has a fall. This accident attention health care system allows the caregiver to sleep without being attentive of the patient or staying awake during the high-risk hours. This is a novel methodology developed by authors to support the caregivers of sleepwalking patients. The study implements only part of the accident attention system, the fall detection module. The future work includes developing the classification model for sleep or wake detection and integrating with the proposed model. The mobile application design for the smart health care of somnambulism patient is also future direction of work.

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