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Remote Patient Health Monitoring Using Iot And Artificial Intelligence

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There is a chance for extremely intelligent and clever IoT-based use cases in the modern period thanks to developments in ICTs like Cyber-Physical Systems (CPS), 5G cellular technology, and the Internet of Things (IoT). As IoT enables Ambient Assisted Living (AAL), Mobile Health (mHealth), and Electronic Health (eHealth), one such use case with a significant social impact is healthcare. People devote a large portion of their income to their health. In addition to resulting in patient deaths, traditional healthcare services are prone to delays, waste of time, and financial loss. When used in conjunction with the IoT's intelligence and prediction capabilities, regular Remote Patient Monitoring (RPM) at home, work, or at a hospital can help individuals who specifically require it overcome obstacles presented by traditional healthcare facilities. Wearable technology, sensor networks, and other digital infrastructure are used in IoT-based RPM can serve as a precursory warning system for approaching situations that, if ignored or care is postponed, could result in serious health problems or even patient death. Doctors can receive real-time patient vital signs through wearable devices (biosensors) with IoT integration. That way, medical professionals can start treating patients right away. The term "RPM" refers to this occurrence, which has the potential to reduce wait times, save healthcare expenses, and enhance patient comfort and service quality. In order to implement a Remote Patient Monitoring System (RPMS) with data analytics capabilities, this paper aims to develop an Internet of Things (IoT) and Artificial Intelligence (AI) enabled framework. We implemented RPM for data collection and proposed an algorithm for disease diagnosis. Our experimental results revealed that our method outperforms existing methods.

Keywords – Remote Patient Monitoring, Data Analytics, Personalized Healthcare, Internet of Things.

1. INTRODUCTION

Due to its impact on individuals and organizations, technological advancements like the Internet of Things (IoT) have gained enormous significance. Other current technologies are utilized in conjunction with IoT technology to realize numerous use cases. For example, in addition to other wireless communication technologies, sensor networks and Radio Frequency Identification (RFID) are essential components of the Internet of Things. IoT applications generate vast amounts of data, which is why this technology is associated with big data and cloud computing [1]. It can also take advantage of edge computing and fog computing technologies [16]. Super markets, healthcare, and transportation are just a handful of the areas that can leverage IoT. But in this work, we concentrate on the use case of remote patient monitoring (RPM) in the healthcare sector. Given that health is wealth, as they say, creative methods of delivering health services are required. Since RPM can save lives and offer healthcare services with little cost or delay, it has the potential to completely transform healthcare delivery in the real world. In India, a large number of VIPs and politicians perished due to improper RPM usage. If that is applied, heart attack-related deaths will cease as these cases increase over time. In a typical approach, there is a delay between the start of treatment and the development of symptoms. Meanwhile, lives are ending for people.

There are numerous RPM systems in use today that address the aforementioned issue, according to the literature. To name a few, it is investigated in [1], [2], and [4] to realize individualized remote healthcare services. An eco-system capable of achieving RPM is required. In addition to data analytics and AI [22], [26], [27], many researchers also took advantage of other technologies, such as wearable technology [1], [9], [11], blockchain technology [15], [16], [21], cloud computing [2], [3], [6], fog or edge computing [16], [28], [32], and wearable technology [1], [9], [11]. RPM has the capacity to have the biggest influence on people's life. IoT and other technologies are used to make it happen. Numerous RPM systems are currently in use, and various technologies are being employed. Consequently, it's critical to determine and obtain information from the state of the creative. Our contributions in this paper are as follows.

1. We proposed an architecture suitable for IoT enabled system for remote patient monitoring that exploits sensors for capturing data.
2. We proposed an algorithm based on MLP and feature engineering that takes UCI data for training and data collected from patient for diagnosis.
3. We built an application to evaluate the performance of the proposed RPM and the results are compared with the state of the art.

The remainder of the paper is structured as follows. Section 2 reviews literature on existing RPM techniques. Section 3 presents our methodology while section 4 presents experimental results. Section 5 concludes our work and throw light on future scope of the research.

2. RELATED WORK

Rejeb et al. [1] IoT progress in healthcare analyzed via review and bibliometric study of 2,990 articles, exposing research focal points, gaps, and upcoming trends. Malche et al. [2] Telehealth and RPM are crucial in pandemic times, offering cost-effective, easy-access patient care. A proposed IoT-enabled device tracks activities and vitals, enhancing remote monitoring efficiency. Alazzam et al. [3] IoT aids in smart health monitoring, tracking mental and physical well-being. Technological advancements address stress, anxiety, and hypertension, enabling early detection for enhanced quality of life. Khan et al. [4] enhance remote patient monitoring, but managing data remains challenging. A proposed visualization system improves real-time monitoring, usability, and satisfaction, boosting healthcare efficiency. Khan et al. [5] The IoT evolves from IoC to CPS, introducing security concerns. An AI-enabled IoT-CPS aids doctors in disease detection efficiently. Bhunia et al. [6] Amid the Covid-19 pandemic, a cloud-based IoT system facilitates remote patient diagnosis, ensuring social distancing and preventing disease spread. Boikanyo et al. [7] RPMS research, vital for human lives, increased amid the pandemic. Challenges include mobility, networks, standardization, and QoS. The focus shifted post-2020.

Yakkala et al. [8] remote monitoring detects health issues early for at-risk populations. CNN deep learning ensures accurate ECG classification, enhancing diagnostic precision. Aljrees et al. [9] Advanced health monitoring combines AI and IoT for real-time tracking of heart patients, improving disease classification with higher accuracy. Kannan et al. [10] ICT advancements, including IoT, 5G, and CPS, enable impactful healthcare applications like RPM. Secure IoT integration enhances remote patient monitoring. Alshammari et al. [11] In crowded regions, healthcare demands are addressed with a real-time patient monitoring system using IoT. Sahu et al. [13] IoT revolutionizes healthcare during the COVID-19 pandemic, enhancing digitalization, data management, and patient monitoring, ultimately improving overall healthcare performance. Zahid et al. [14] IoT-based asthma monitoring tracks heart rate, temperature, air quality. Efficient data storage and patient-doctor communication improve healthcare services. Rahman et al. [15] Post-Covid patient care is crucial due to complications. IoT-based monitoring with ML analytics aids in remote health management, especially in rural areas. Kumar et al. [16] The IoT transforms healthcare with a smart patient monitoring system and intelligent medication management for home-centric healthcare services.

Kabir et al. [17] proposed IoT-based system uses sensors for remote health monitoring, detecting heart conditions, fever, and abnormalities, providing real-time feedback and connecting to doctors for further diagnosis. Rafa et al. [18] addresses asthma and COVID-19 challenges in Bangladesh, emphasizing telemedicine and real-time monitoring. The prototype enhances healthcare accessibility and awareness. Wang et al. [19] The IoT health monitoring system addresses COVID-19 issues with real-time remote tracking, easing healthcare loads, and improving pandemic management. Gomare et al. [20] wearable IoT device monitors health metrics, stores data in the cloud, allowing remote access, ensuring continuous monitoring with alerts. Uddin et al. [21] introduces an IoT-based patient monitoring system, offering real-time health monitoring, critical condition detection, and remote accessibility for healthcare professionals. Sood et al. [22] proposed IoT-based fog computing system enhances real-time patient health monitoring, ensuring quick processing and accurate event classification for effective healthcare delivery. Moghadas et al. [23] introduces an IoT-based fog computing system for real-time health monitoring, specifically focusing on cardiac arrhythmia diagnosis using the KNN algorithm. Jeyaraj et al. [24] introduces an IoT-based Smart-Monitor for automated physiological signal monitoring, achieving a 97.2% accuracy in prototype experiments, ensuring reliability.

Thaha et al. [25] proposed low-cost, portable E-health recording system uses IoT for real-time health parameter monitoring and cloud storage for accessibility. Alshamrani et al. [26] explores the integration of IoT and AI in smart cities, emphasizing health applications, models, and technologies for remote healthcare monitoring. Karame et al. [27] explains fingerprinting attacks on SDN networks, demonstrating the high success probability. A proposed countermeasure effectively mitigates these attacks. Mathew et al. [28] proposes real-time remote patient monitoring with Raspberry Pi 3, transmitting data to a website accessible worldwide. It minimizes costs and personnel. Chatterjee et al. [29] The IoT-based health monitoring system offers real-time data collection, reducing errors, minimizing space, and providing alarms, notifications, and automated appliance control. Liang et al. [30] explores the efficiency of a solid cylinder dielectric resonator antenna (CDRA) in generating orbital angular momentum (OAM) waves. The simulations validate its potential for overcoming bandwidth issues in OAM devices, with high radiation efficiency at specific frequencies.

3. PROPOSED SYSTEM

The proposed Remote Patient Monitoring System (RPMS) architecture leverages IoT technology to monitor and transmit patient health signals for real-time analysis and anomaly detection. Different sensors capture various physiological signals from the patient. The Heart Rate Monitor sensor measures the patient's heart rate in beats per minute (BPM). Blood Pressure Sensor (BPS) measures the systolic and diastolic blood pressure values. ECG (Electrocardiogram) Sensor captures the electrical activity of the heart, which is crucial for monitoring the heart's rhythm and identifying issues like arrhythmias. Temperature Sensor measures the body temperature of the patient. These sensors are attached to the patient, and their readings provide continuous data that will be processed in real-time for monitoring purposes.

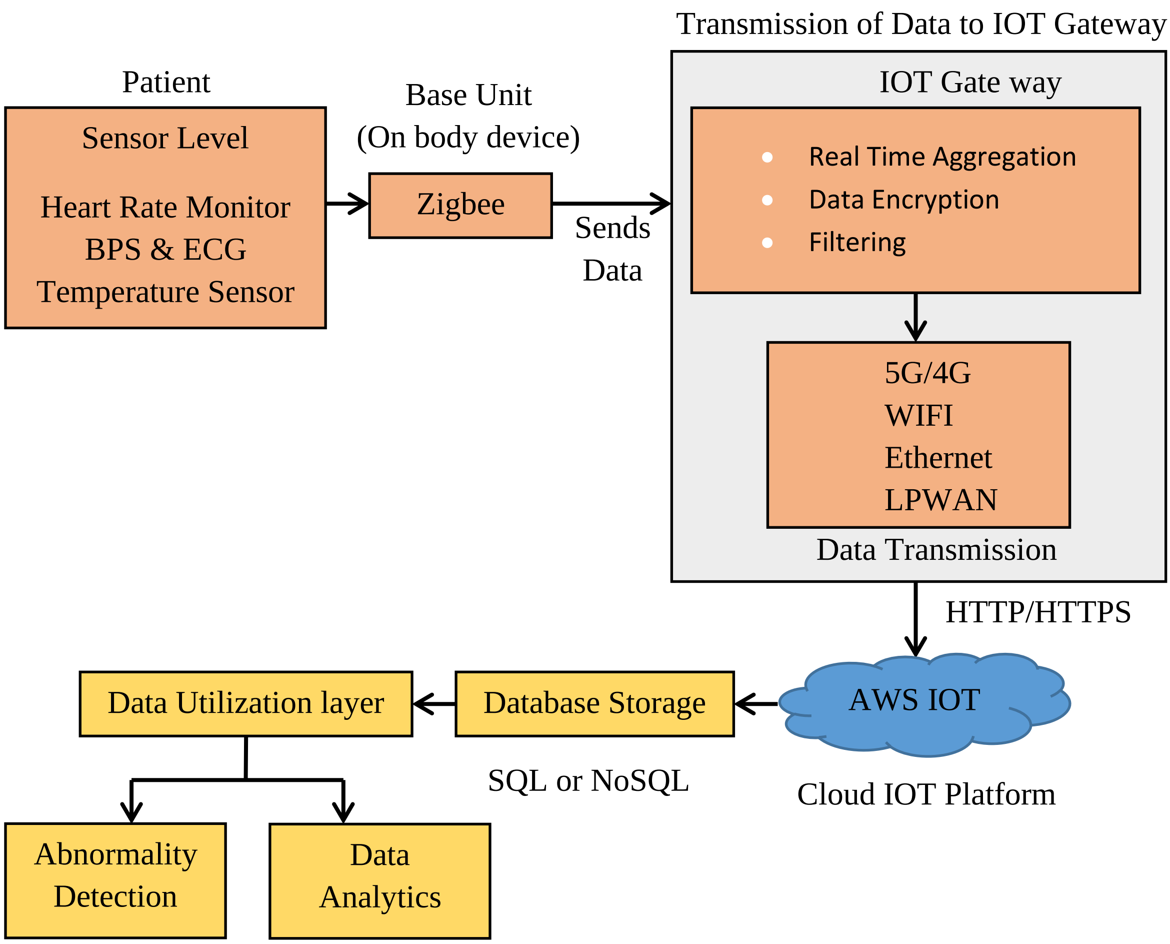

Figure 1: Proposed system

The data from the sensors is transmitted to the IoT Gateway via Zigbee, which is a low-power, short-range wireless communication protocol commonly used in IoT networks. It enables reliable communication between the sensor nodes and the gateway by creating a mesh network, which is beneficial for transmitting data efficiently in a hospital or home monitoring environment. The IoT Gateway is the central hub responsible for processing and transmitting the sensor data to the cloud. It performs three key tasks: The gateway aggregates the data from various sensors in real-time to form a complete dataset. This prevents data loss and ensures accurate monitoring. Data Encryption ensures the security and privacy of sensitive patient data, the gateway encrypts the information before transmitting it to prevent unauthorized access or tampering. Not all data is relevant for real-time analysis. The gateway filters out noise and redundant data, ensuring that only important, relevant data is sent to the cloud.

The IoT Gateway uses multiple communication protocols for data transmission to the cloud or local servers. Cellular networks are used for high-speed data transmission, especially when mobility or remote monitoring is involved. Wi-Fi provides wireless connectivity within a home, hospital, or other local environments. Wired transmission can be used in hospitals or fixed installations where a more stable connection is needed. Low Power Wide Area Network technology is used for low-power, long-range communications, making it ideal for devices that need to send small amounts of data over long distances, often in remote areas. The patient data is then transmitted to AWS IoT, which is a cloud platform by Amazon that handles the storage, processing, and real-time analysis of IoT data. AWS IoT provides several essential services for this system, including: AWS IoT stores the data in secure databases (such as Amazon DynamoDB or S3) for further processing and historical analysis. AWS ensures that the data remains secure during transit and at rest, protecting sensitive patient information. With AWS IoT services like IoT Analytics or AWS Lambda, real-time insights and alerts can be generated, allowing healthcare professionals to intervene quickly in case of abnormalities. Data Utilization Layer deals with the processing and utilization of the collected and transmitted data. It has two main functions: AI/ML models (like LSTM for time-series data) analyze the data for anomalies, such as irregular heartbeats, abnormal blood pressure spikes, or body temperature deviations.

When an anomaly is detected, the system can alert healthcare providers or the patient. Advanced analytics are applied to the data to generate reports, predict future health events, and understand patient trends over time. Data analytics also helps in long-term healthcare management, making the system more proactive than reactive. The data transmitted to the cloud (AWS IoT) or on-premise systems is stored in structured or unstructured databases depending on the volume and nature of the data. The stored data serves multiple purposes: Doctors and healthcare providers can review past patient data to make informed decisions. For the AI models that detect abnormalities, the historical data is crucial for training and improving the model's prediction accuracy. The architecture demonstrates how patient vitals are continuously monitored using IoT sensors, and how that data is securely transmitted and stored using cloud-based services like AWS IoT. The IoT Gateway aggregates, filters, and encrypts the data before sending it to the cloud via different transmission technologies like 5G, Wi-Fi, Ethernet, or LPWAN. The data is then processed for abnormality detection and analytics using AI/ML models, which help in real-time monitoring and predictive healthcare.

For data analytics we proposed a feature engineering methodology that is based on 3 filter methods. A Multilayer Perceptron (MLP) along with feature engineering is used for better performance.

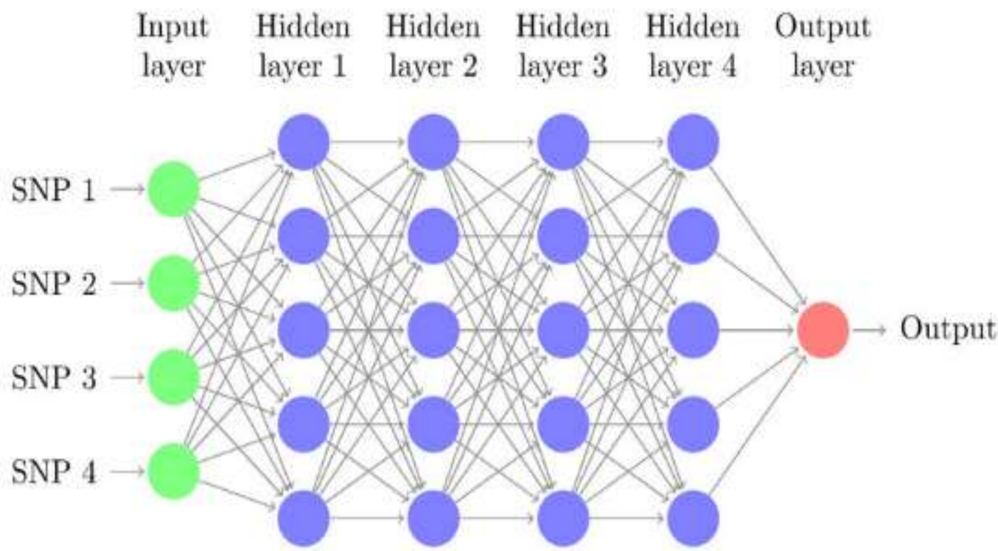

Figure 2: MLP model with four hidden layers

The MLP model is based on neural network. It has potential for learning from data and predict class labels. In this paper, we used it along with feature engineering. Our feature engineering approach is based on Figure 3. We combined three filter based methods for effective feature selection.

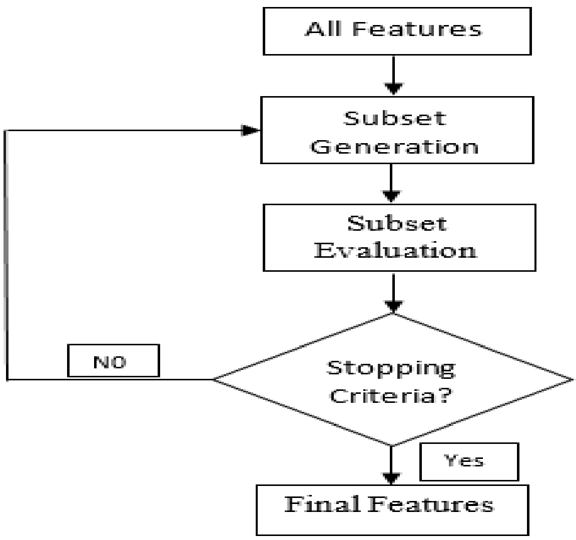

Figure 3: General feature selection method

Based on the generic approach for feature selection, we used three filter methods namely Fisher index [40], T-test [41] and Kullback-Leibler divergence [42]. These three methods are expressed in Eq. 1, Eq. 2 and Eq. 3.

$$F(i) = \left| \frac{\mu_1(i) - \mu_0(i)}{\sigma_1^2(i) - \sigma_0^2(i)} \right| \quad (1)$$

$$t(i) = \left| \frac{\mu_1(i) - \mu_0(i)}{\sqrt{\frac{\sigma_1^2(i)}{n_1} + \frac{\sigma_0^2(i)}{n_0}}} \right| \quad (2)$$

$$KL(p, q) = \sum_i p_i \log_2\left(\frac{p_i}{q_i}\right) \quad (3)$$

Our feature engineering method combines these three measures to have better performance in choosing features that to class label prediction.

Algorithm: IoT and AI Enabled Remote Patient Monitoring (IA-RPM)
Input: Patient data obtained through IoT P, UCI data D
Output: Diagnosis results R, performance statistics S

1. Begin
2. D’🡨PreProcess(D)
3. P’🡨PreProcess(P)
4. F🡨FeatureSelection(D’)
5. F1🡨FeatureSelection(P’)
6. Train MLP with F
7. R🡨Diagnosis(model, F1)
8. S🡨Evaluation(R, ground truth)
9. Display R
10. Display S
11. End

Algorithm 1: IoT and AI Enabled Remote Patient Monitoring (IA-RPM)

As presented in Algorithm 1, it takes UCI data from [39] for training purpose and patient data collected using IoT is used for testing. MLP along with feature selection is used for diagnosis. Performance is evaluated using accuracy metrics. Metrics obtained from the confusion matrix depicted in Figure 4 are used to assess the hearts disease prediction performance of the proposed system and state-of-the-art techniques. In order to train models, training data is gathered from [39].

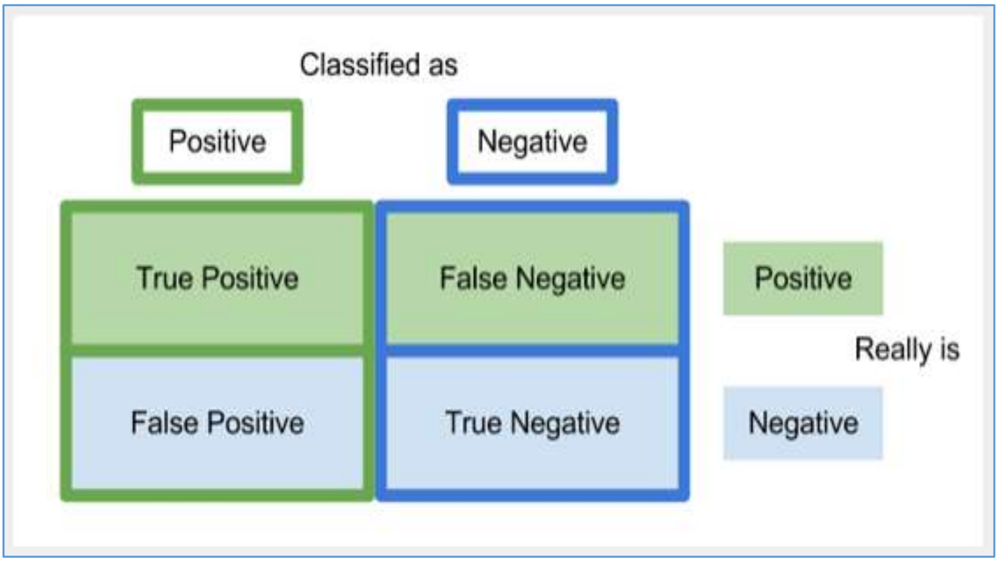

Figure 4: Confusion matrix

The evaluation comprises four instances, each based on the ground truth and forecast value. An example of a true positive is one in which the model identified the sample as positive (heart abnormalities). Real negatives are samples that the model identified as negative and that have no cardiac abnormalities. A false positive is a sample that the model saw as positive even though it was negative (no cardiac abnormalities). A false negative is a sample that the model identified as negative but was actually positive (heart abnormalities). Accuracy is the performance metric, as expressed in Eq. 4, used for evaluation.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \qquad (4)$$

A value between 0 and 1 is produced by these measurements. A higher resultant value denotes improved performance in the prediction of heart disease.

4. RESULTS AND DISCUSSION

We conducted an empirical study using a smartphone running the Android operating system. The assessment of the system involves a patient. Patient stands 170 centimeters tall. tM = 9, tl = 60, tGT = 3, and tAT = 4.2 are additional values that were taken into consideration for the empirical study. Data from a gyroscope and accelerometer were employed in fall detection algorithms. Android mobile devices came with these sensors built in. Android OS-powered smart watch was used to record blood pressure and heart rate. That system has the capacity to identify falls that might occur in any direction, including forward, backward, left, and right.

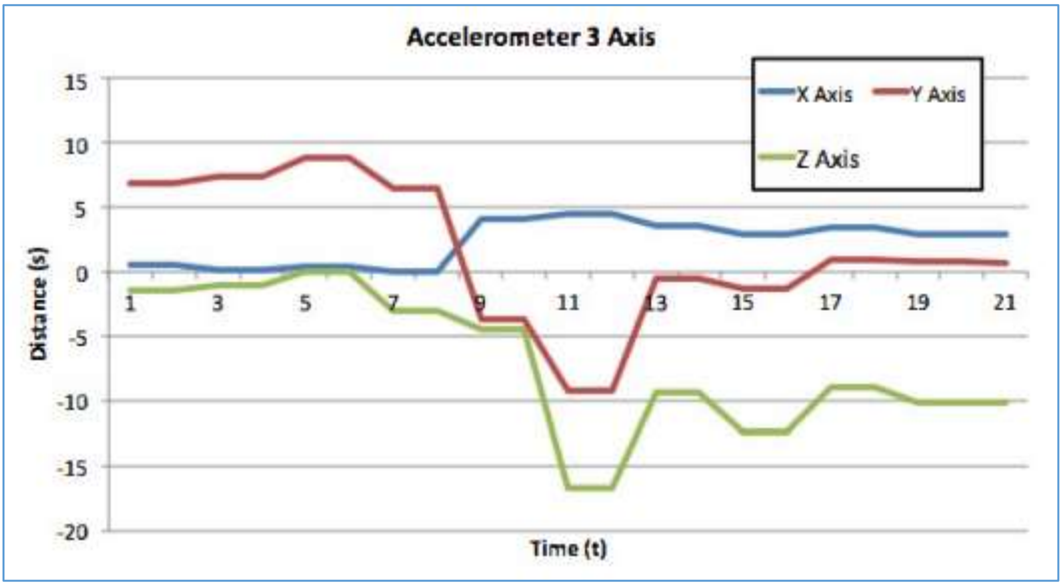

Figure 5: Raw data of accelerometer

Data from accelerometers are shown for three axes over time vs distance in Figure 5.

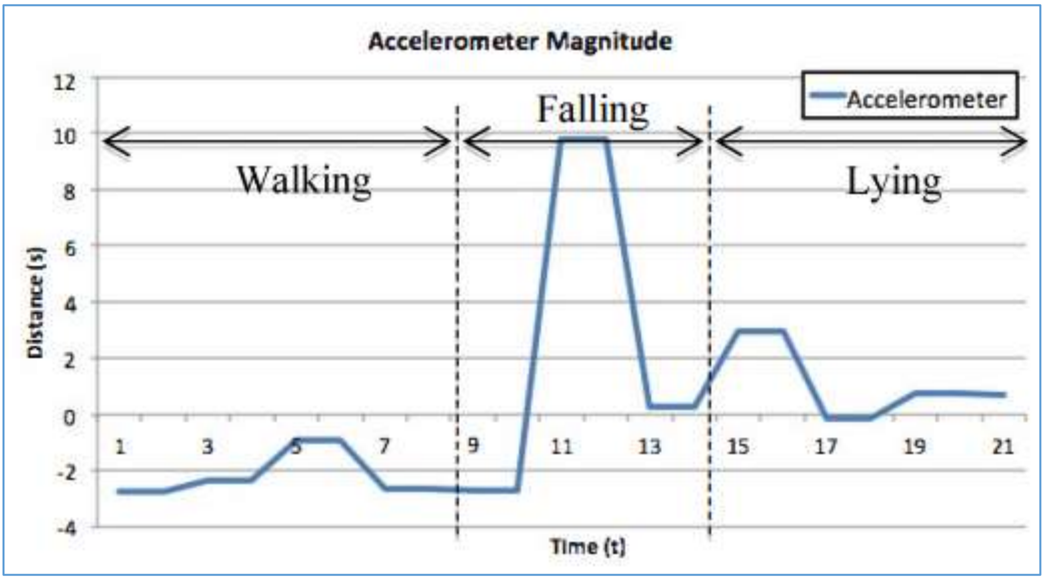

Figure 6: Magnitude data of accelerator

To identify falling, accelerometer magnitude data related to time versus distance are provided, as shown in Figure 6.

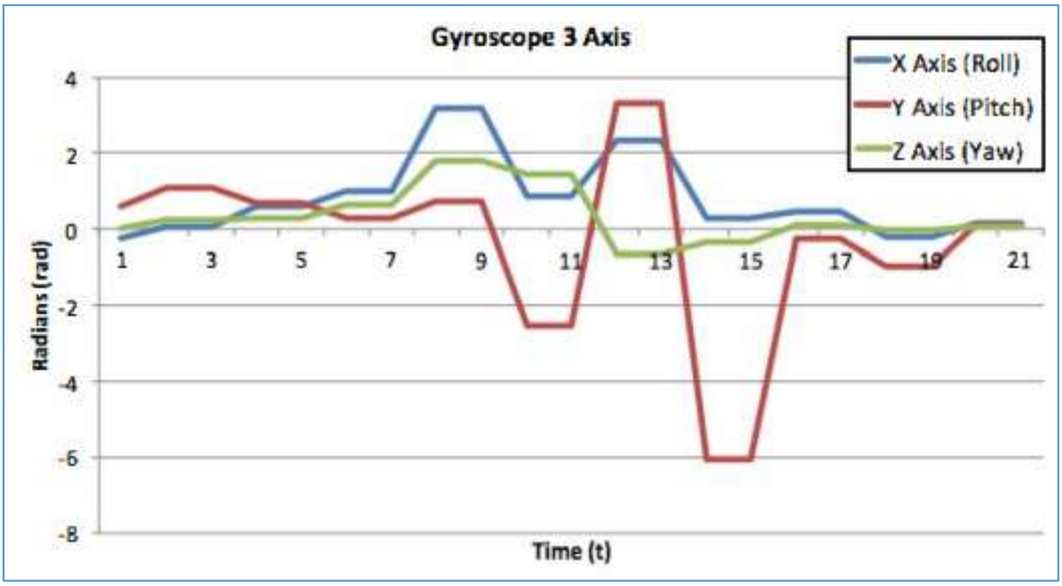

Figure 7: Raw data of Gyroscope

Rough gyroscope data for three axes and time versus radians are shown in Figure 7.

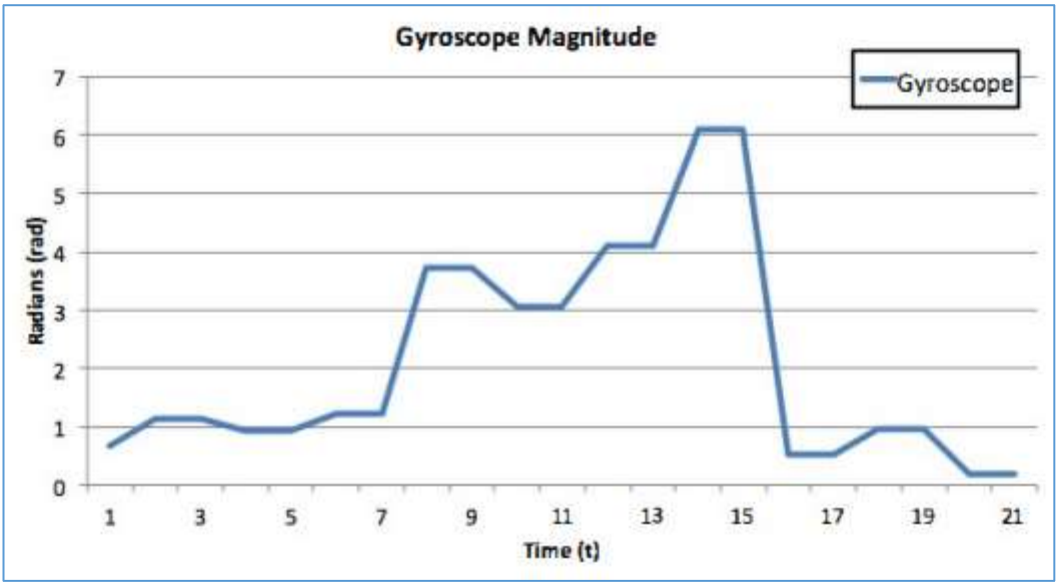

Figure 8: Magnitude data of gyroscope

As seen in Figure 8, falling is determined using gyroscope magnitude data related to time vs radians.

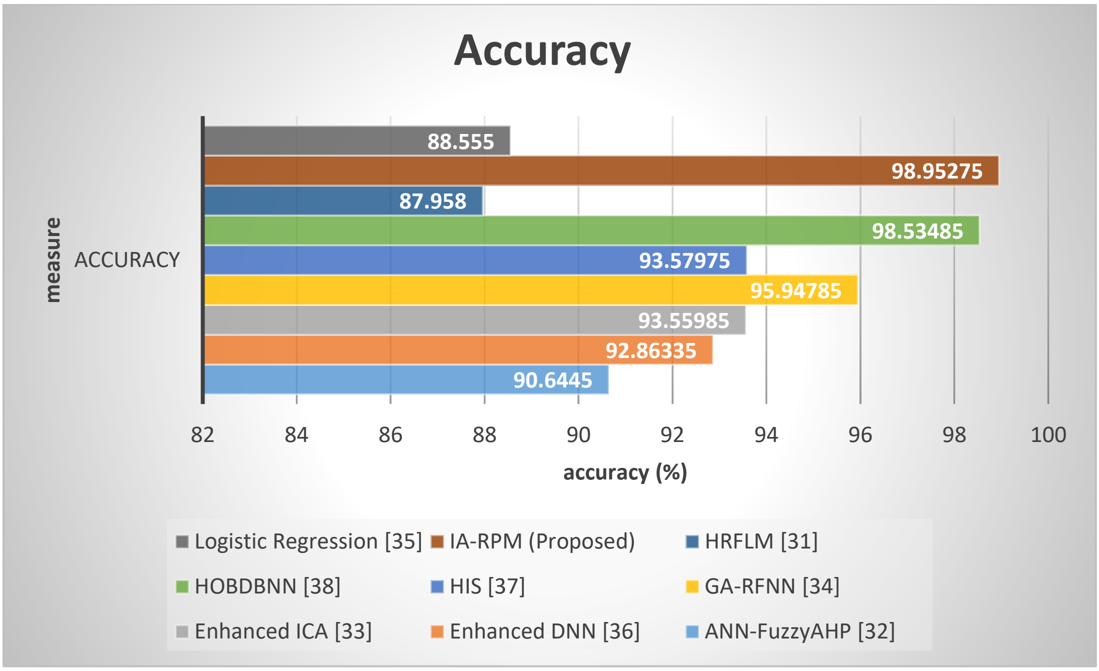

Figure 9: Accuracy comparison

As presented in Figure 9, accuracy in health data analytics exhibited by different models is provided. Higher in accuracy relates to better performance of the model in diagnosis. The model used in [35] achieved 88.55% accuracy, model in [31] 87.95%, model in [38] 98.53%, model in [37] 93.57%, model in [34] 95.94%, model in [33] 93.55%, model in [36] 92.86% and the model in [32] achieved 90.64% accuracy. Highest accuracy is achieved by the proposed algorithm named IA-RPM with 98.95% accuracy.

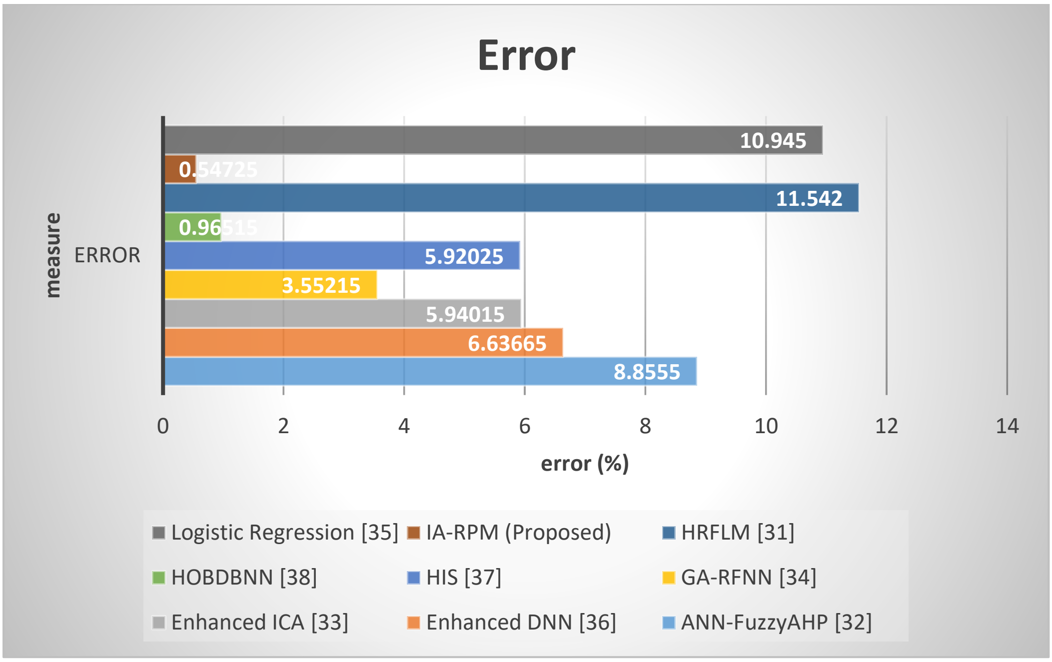

Figure 10: Error comparison of different models

As presented in Figure 10, error in health data analytics exhibited by different models is provided. Lower in error relates to better performance of the model in diagnosis. The model used in [35] achieved 10.94 error, model in [31] 11.54, model in [38] 0.96, model in [37] 5.92, model in [34] 3.55, model in [33] 5.94, model in [36] 6.63 and the model in [32] achieved 8.85 error. Lowest error is achieved by the proposed algorithm named IA-RPM with 0.54. Experimental results revealed that the proposed model shows better performance over the existing models.

5. CONCLUSION AND FUTURE WORK

In this paper, we proposed an IoT enabled AI system for RPM and disease diagnosis. Our system is based on IoT for capturing patients' data and AI for disease diagnosis. Our framework is cloud-assisted and scalable. It is based on cost-effective sensors present in wrist watch and smart phone. The proposed system exploits MLP model for disease diagnosis. The model is supported by our hybrid feature selection method which is based on three filter methods. We proposed an algorithm to realize a model along with feature engineering for better diagnosis. We compared our results with many state of the art models. Our results showed that the proposed method showed highest accuracy with 98.95% accuracy. In future, we intend to improve our system with more sensors for taking patients' vital signs and also explore deep learning models for disease diagnosis.

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