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An IoT Based Healthcare System for Remote Patient Monitoring towards Real Time Treatment

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Abstract: 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 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: *Internet of Things, Machine Learning, Remote Patient Monitoring, Healthcare, Artificial Intelligence*

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 area s that can leverage IoT. But in this work, we concentrate on the use case of 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.

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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

Jamil et al. [1] proposed a secure and efficient Blockchain-based Fog-enabled remote patient monitoring system for IoT devices, enhancing data security and response time. Future works include using real healthcare datasets, adding prediction modules, integrating with a body area network, and improving the fog layer with modern tools like federated learning. Khan et al. [2] proposed a real-time health monitoring system for COVID-19 patients, utilizing digital twins in Internet of Robotic Things (IoRT) with a Virtual Reality (VR) interface. The system ensures safety and accuracy in remote monitoring. Future work includes autonomous navigation, AI implementation, and improved synchronization for extended distances. Akkas et al. [3] explored IoT's impact on healthcare, emphasizing Wireless Body Area Networks (WBANs) for patient monitoring. It details a ZigBee-based prototype, proving reliability and performance superiority. Chen et al. [4] IoT transforms healthcare, especially in assisted living for the aging population. Advances in IoT tech enhance in-home health monitoring systems, emphasizing challenges and future directions. Taiwo et al. [5] The COVID-19 pandemic necessitates remote health monitoring. Proposed smart home healthcare supports patients through IoT, easing hospital visits, and improving quality of life.

Howson et al. [6] Utilizing block chain-based smart contracts enhances security in IoT healthcare, ensuring real-time monitoring and HIPAA-compliant notifications, resolving vulnerabilities. Kaur et al. [7] proposed an IoT-based healthcare system utilizing machine learning, focusing on diseases like heart issues and diabetes. The proposed system enhances patient-doctor interaction. Experimental results, employing algorithms such as K-NN, SVM, Decision Trees, Random Forest, and MLP, achieved high accuracy. The study emphasizes data security implications in IoT frameworks. Wadi et al. [8] IoT, an integral part of healthcare, enables low-cost monitoring through wearable devices, wireless channels, and sensors, revolutionizing patient care. The study explores IoT's role, emphasizing improved diagnostics and service quality. Patil et al. [9] investigated IoT integration into WBAN for healthcare, covering security, privacy, current architectures, applications, and future research. Baker et al. [10] focused on a smart healthcare monitoring system (SW-SHMS) for remote elderly care. SW-SHMS utilizes wearable sensors, cloud analysis, and real-time detection for early intervention. The system demonstrates efficient performance, low latency, and minimal packet loss, contributing to improved healthcare services. Future enhancements include AI integration, a recommendation system, and Fog computing for faster data processing at the network edge.

Reference	**Techniques**	**Advantages**	**Limitations**
[2]	Utilizing big data, cloud computing, and the IoT to monitor patient health.	It is highly efficient, scalable, and secure manner.	Greater emphasis on theory. not a sensible strategy.
[4]	IoT integration with a Raspberry Pi 3 for remote patient monitoring.	Patient vital signs are monitored remotely.	For the necessary intelligence, a data analytics module is still needed.
[9]	mHealth, eHealth, RPM, and wearable technologies.	Patients can obtain healthcare at a reasonable cost.	more theoretical in character. Not a sensible strategy.
[11]	RPM, RFID, and ontology-based methods.	keeping patients private while keeping an eye on them remotely.	It lacks data analytics and machine learning.
[12]	techniques for monitoring patients remotely.	gives a summary of the various methods for remote patient monitoring.	We still have not achieved a medical knowledge-based system.

[19]	RPM driven by IoT	the quality of service by enabling remote patient monitoring.	Security and privacy are the main concerns.
[27]	RPM was achieved via a mixed strategy.	more rapid and precise RPM resolution.	Depending on the simulated data and artificial intelligence.
[32]	RPM and alerting strategies made possible by IoT.	Instantaneous statistics are enhanced via temporal mining.	Improvements are required for a real-time warning system.
[33]	IoT, RPM-focused data mining, and fog computing.	precise and trustworthy diagnosis.	For varying application demands, it still requires improvement.
[36]	Internet of Things and semantic technologies for tailored medical treatment.	Medical records are accessible to patients.	There is no usage of data mining.
[37]	RPM with Internet of Things	enhanced medical care	not using the necessary data analytics.

Table 1: Summary of important findings

Table 1 shows summary of important findings. Souri et al. [11] proposed an IoT-based student healthcare monitoring model using smart technologies and machine learning for efficient risk detection. Hassan et al. [12] explored machine learning's role in IoT, focusing on applications in healthcare, smart grids, vehicular communications, and more. Albadr et al. [13] discussed the significance of IoT, cloud, and machine learning in healthcare, focusing on voice pathology monitoring challenges and solutions. Philip et al. [14] IoT transforms healthcare with in-home monitoring for an aging population. Despite advancements, challenges persist, requiring attention to technology acceptance, adoption, and ethical concerns. Klaib et al. [15] Eye tracking, vital for various applications, is advancing with modern approaches like ML, IoT, and cloud computing, ensuring efficiency and accuracy.

Doro et al. [16] found that IoT demands proactive security solutions. A secure-by-design vision, utilizing machine learning and software-defined networking, is essential. Mohanty et al. [17] explored Cognitive Internet of Medical Things (CIoMT) for smart healthcare during COVID-19, emphasizing efficient spectrum management and rapid, cost-effective diagnostics. Bello et al. [18] IoT integration with medical systems enhances healthcare services. Connectivity, crucial for digital healthcare, benefits from IoT, ensuring real-time data for informed decisions. Renta et al. [19] iTaaS, an innovative framework, merges cloud, IoT, and smart sensors for efficient data transmission. Proven in remote health monitoring. Bhatt et al. [20] Health care IoT, driven by advanced technology, improves patient safety, reduces costs, and enhances accessibility. Machine learning aids efficient data analysis.

Luo et al. [21] Deep learning aids cardiac image processing for IoT-based wearable devices. A self-adaptive power control enhances energy efficiency for elderly healthcare. Gupta et al. [22] highlights the significance of IoT in health systems, especially during the COVID-19 pandemic. A proposed model integrates 1D biomedical signals for remote patient monitoring, achieving 96.33% accuracy and efficient power consumption. Amin et al. [23] addressed the need for advanced smart healthcare frameworks with 5G, IoT sensors, and edge computing. It explores edge intelligence challenges and proposes improvements for healthcare services, emphasizing IoT applications in edge platforms. Ghosh et al. [24] introduced an IoT and deep learning-based healthcare framework for sustainable smart cities. The proposed DHNN achieves high accuracy (97.6%), precision (97.9%), and sensitivity (94.9%) in health data analysis, outperforming other classifiers. Task scheduling algorithms enhance efficiency, making it suitable for various healthcare domains. Javadi et al. [25] proposed a secure remote health monitoring model using lightweight block encryption in cloud-based IoT platforms. The K-star classification achieves the best results. Future work includes real-world implementation, model enhancement, and exploring disease-infection relationships, particularly related to COVID-19.

Hassan et al. [26] proposed a hybrid context-aware model for home patient supervision, combining local and cloud components. It effectively monitors patients, especially those with blood pressure disorders, ensuring real-time analysis and emergency detection in imbalanced datasets. The model proves fast, accurate, and fault-tolerant, offering potential for broader healthcare applications. Qung et al. [27] addressed challenges in IoT and WSN, emphasizing the role of Machine Learning (ML) in enhancing QoS. It introduces ML categories, algorithms, applications, and research challenges, providing a comprehensive overview and future research directions. Kumar et al. [28] proposed an IoT UAV-based scheme for COVID-19 detection, utilizing thermal sensors and face recognition. Improvements include indoor scanning, diverse datasets, and online learning integration. Durga et al. [29] discussed the development of an IoT-based smart edge system for global health, addressing challenges through remote health monitoring. Islam et al. [30] introduced a smart waste management system using IoT and AI, employing LoRa for data transmission. TensorFlow facilitates real-time object detection and classification in waste bins. The system monitors filling levels, location, and personnel identification for efficient waste segregation. The implementation successfully enhances waste management efficiency with potential for further improvements.

3. PROPOSED FRAMEWORK

Figure 1 shows the suggested system called the IoT-driven Remote Patient Monitoring System. The goal of this system's design and development is to lessen the danger of sudden cardiac arrest, brain stroke, and heart attack by providing real-time or early disease identification. IoT sensors are able to be included in the suggested system in order to continuously gather patient vital signs. The blood pressure sensor, heart rate sensor, accelerometer, and gyroscope are the three sensors that were utilized in this. The patient's blood pressure is measured by the first sensor, and their heart rate is detected by the second. The third and fourth devices gather information aimed at identifying the patient's risk of falling. Fall detection and real-time cardiac disease diagnosis are made possible by this IoT-integrated real-time sensor capability. The public cloud hosts the real-time data that is collected by IoT sensors. Also stored in the cloud is a benchmark dataset for the identification of heart disease. This was extracted from the UCI repository [39]. For real-time patient monitoring, live sensor data from the patient is analysed. Heart rate, blood pressure, and patient falls are all monitored.

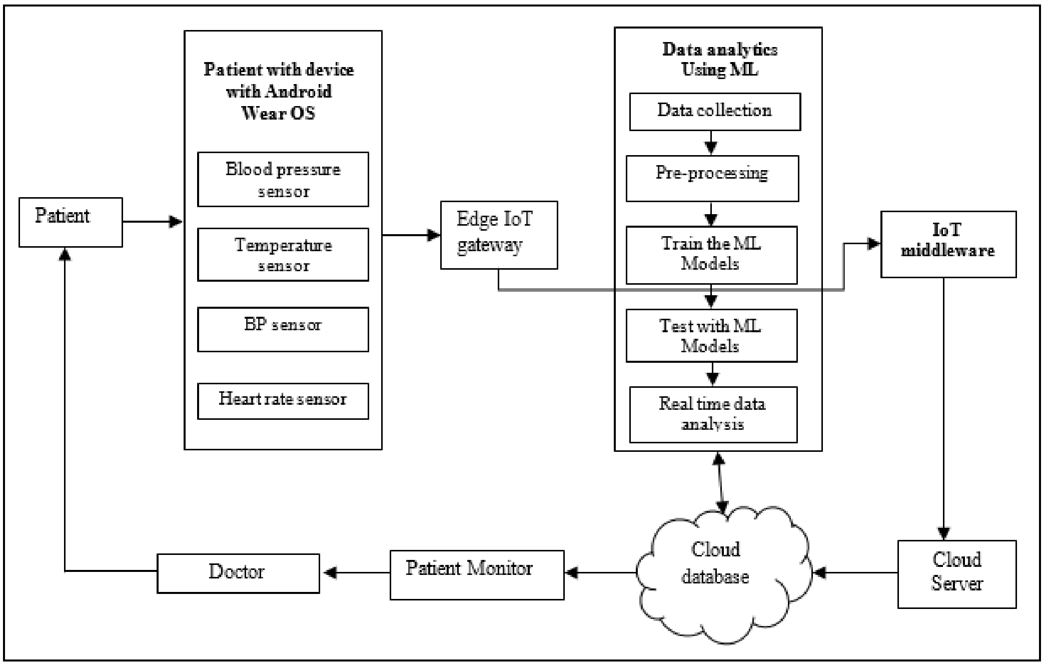

Fig 1: Architecture of the proposed system

Both the patient's family and the doctor are informed of these facts, including any irregularities. The suggested system includes the ability to gather patients' vital signs using traditional methods and transmit them to the system in addition to live monitoring. Next, in order to automatically diagnose cardiac illness, the system uses supervised learning of the specified patient. Utilizing UCI data, the system is trained to produce the appropriate knowledge model. With standard patient data, this knowledge model is maintained and used in future heart disease detection. It is a disease detection method made possible by artificial intelligence. 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.

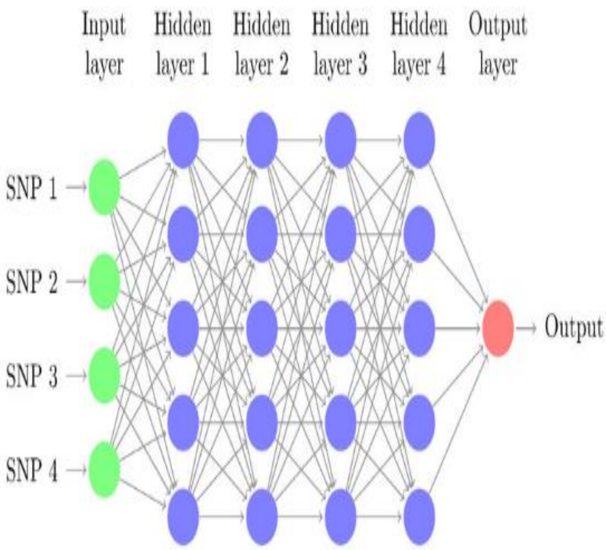

Fig 2: MLP model with four hidden layers

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.

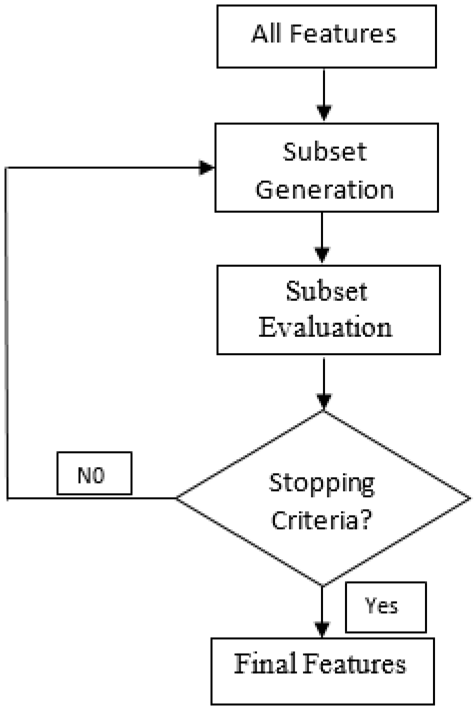

Fig 3: General feature selection method

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.

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

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

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

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].

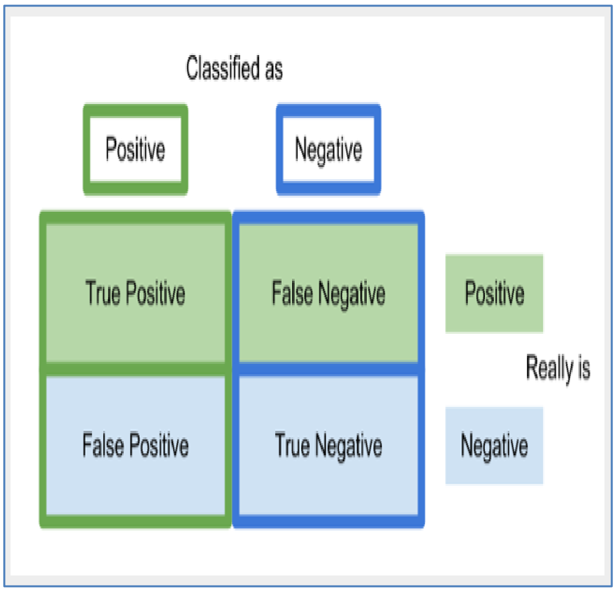

Fig 4: Confusion matrix

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.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

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.

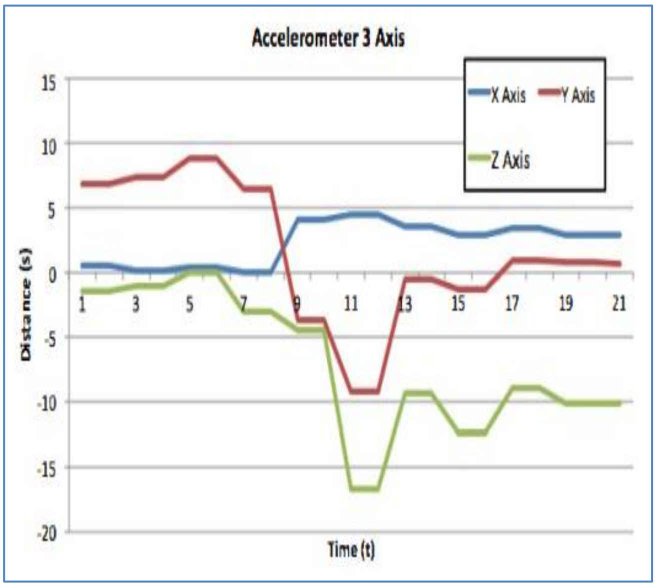

Fig 5: Raw data of accelerometer

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

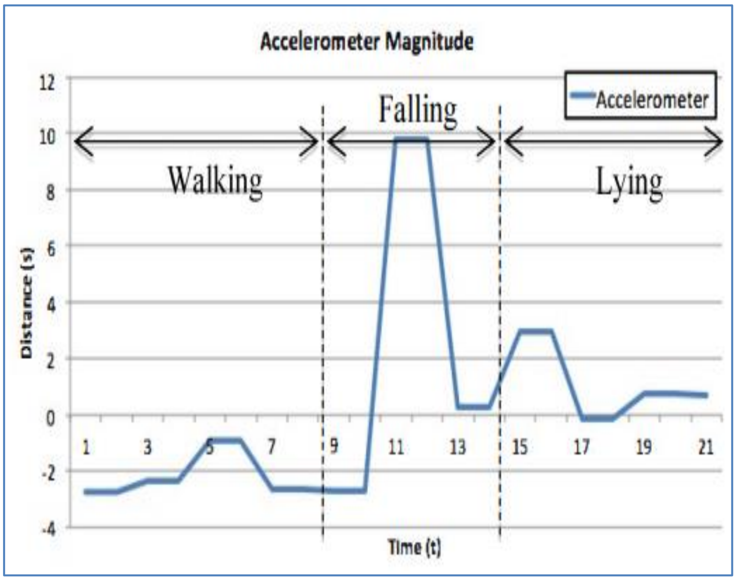

Fig 6: Magnitude data of accelerator

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

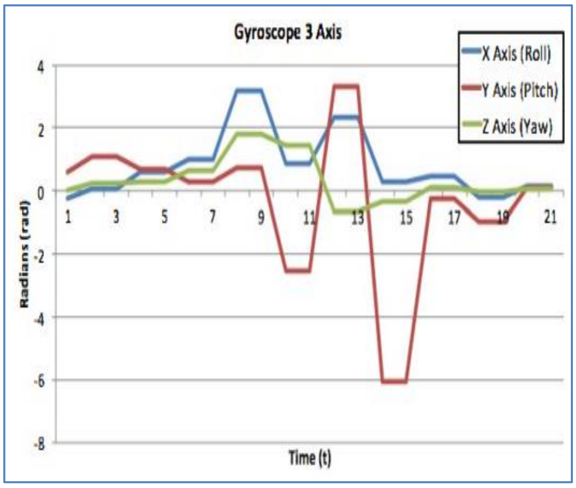

Fig 7: Raw data of Gyroscope

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

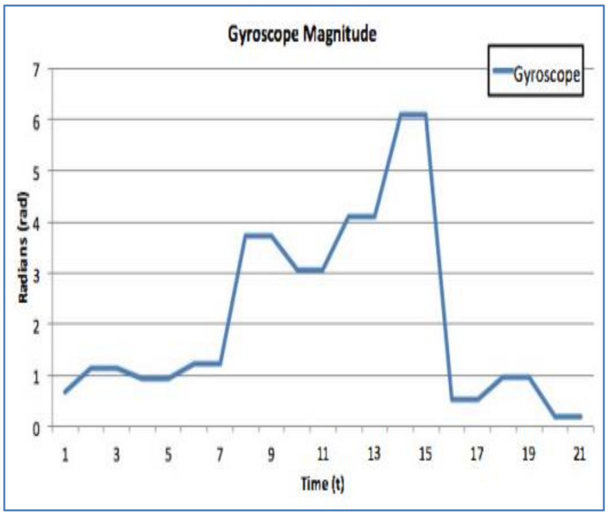

Fig 8: Magnitude data of gyroscope

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

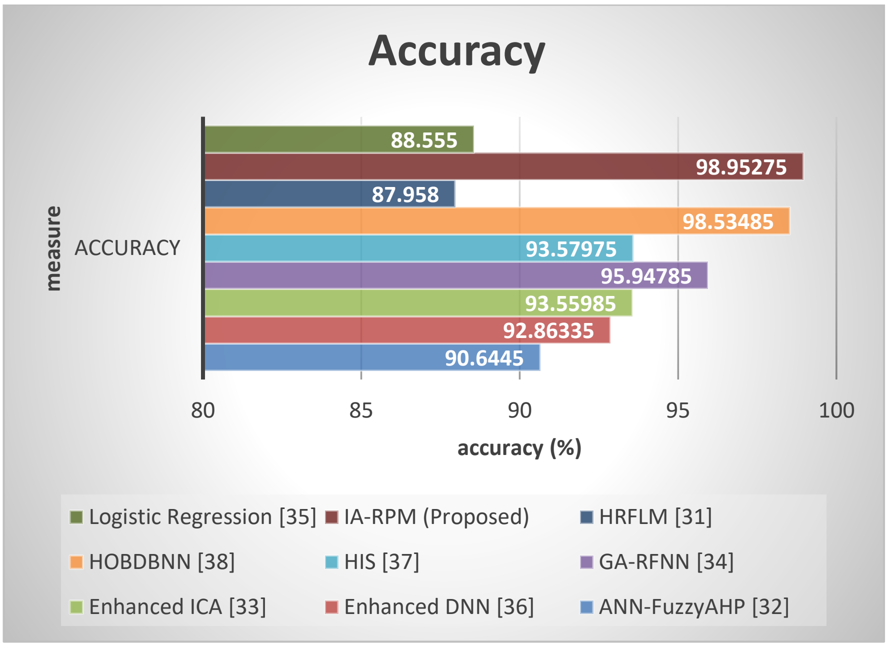

Fig 9: Accuracy comparison

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.

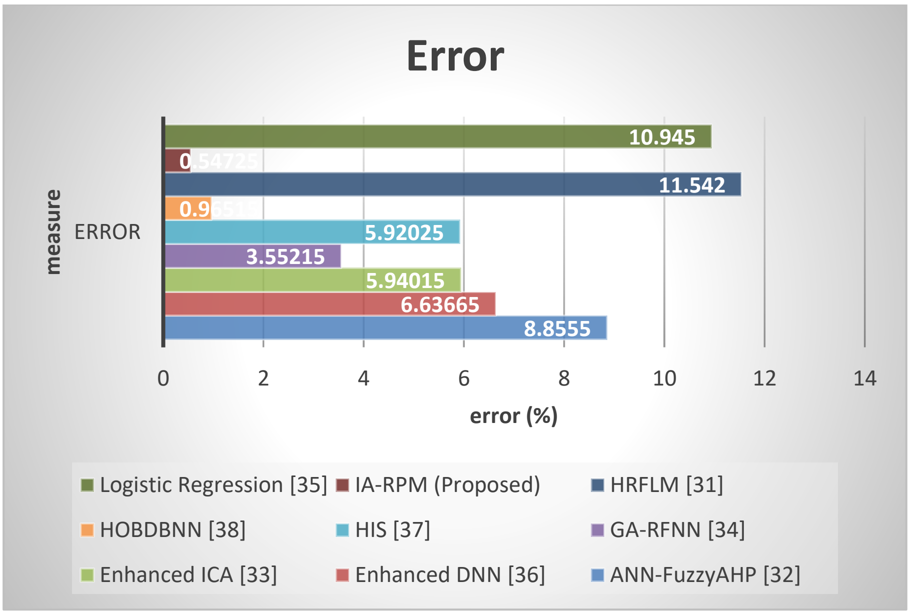

Fig 10: Error comparison of different models

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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