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Empowering Health and Well-being: IoT-Driven Vital Signs Monitoring in Educational Institutions and Elderly Homes Using Machine Learning

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ABSTRACT- IoT-based EHRs use machine learning technology to automate real-time patient-centered records more securely for authorized users. *Background*: In this era of pandemics, predictive healthcare systems are necessary for private and public healthcare delivery to predict early cancer, COVID-19, hypertension, and fever in Educational Institutions and Elderly Homes. IoT-Based EHRs bring healthcare delivery to the doorsteps of educational home facilities users, thereby reducing the time required to access healthcare and minimizing direct physical interaction between individuals seeking healthcare and their providers. Method: This research work proposed a real-time intelligent IoT-based EHR system that generates vital signs of students within the educational environment using contactless sensors (Raspberry Pi Noir Camera, rPPG camera) and contacted wearable sensors composed of enzymatic sensor, immunogens, and Nano sensors to detect cancer (Leukaemia). AFTER CAPTURING THE PHYSIOLOGICAL DATA, THE in-build EWS plots system determines the condition and further triggers the criticality (abnormality) in health status. *Discussion*: For effective health status prediction by the proposed plan, the vital sign dataset was used to train a model for the proposed method. Among the best-performing models, the random forest algorithm proved a better model, with an accuracy of 99.66% and an error rate of 0.34%. *Conclusion*: The Home HMS seeks to improve health prediction in institutional homes for users' overall well-being.

General Terms: Internet of Things, Machine Learning Algorithms. Smart Health Monitoring.
Keywords: Internet of things, EHRs, IoT-based, EHR, Machine Learning, Educational Institutions and Elderly Homes, Health Monitoring.

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1. INTRODUCTION

A recent attempt to computerize the automation of health detections for critical health conditions such as cancer, COVID-19, fever, and hypertension, among others, has necessitated the investigation into predictive systems. IoT-based Electronic Health Records (EHRs), also referred to as IoT-based Electronic Medical Records (EMRs), are a combination of hardware (servers, computers, mobile devices), IoT devices (actuators, sensors, or wearables), and software that constitute a warehoused of real-time data which provide essential healthcare services to physicians (healthcare professionals) and patients if adopted by healthcare organizations [1].

Homes within institutions lack the necessary technologies to prolong users' lives through comprehensive real-time monitoring of students and other residential users. Homes within educational institutions often encounter health-related challenges mainly because these institutions lack the technology to solve these challenges. According to [2,3], lack of technical infrastructure, lack of logical or physical accessibility, and lack of exposure to the systems are the significant challenges in adopting EHRs amidst the challenges of privacy and security [1]. IoT-based EHRs using ML, if implemented in educational homes, will modernize the residence health-wise, thereby ensuring students' overall well-being and preventing unpredictable sicknesses that could lead to death.

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IoT has come to bless information and technology [4]. IoT is a technology that aids in gathering data from an external environment through a gateway into a database using sensors, controllers, interfaces, actuators, and buses [5]. The sensors generate data from the external behaviors based on parameters set and send it into the interpretation systems for human understanding. IoT technology is rapidly taking over the homes, healthcare, transportation, and manufacturing world today since IoT brings life into all external features like doors, cars, and patient monitoring systems in and out of ecology.
Machine learning uses a set of rules, also known as algorithms, to train data or collected datasets in real time or from a data warehouse (database or dataset repository). According to [6], the fundamental explanation of ML is when a set of programs (algorithms) is executed to interpret the input; the algorithm uses the inputted data to present the output.

In ML, the algorithms are simple terms meant to make a system or devices that deploy them to learn from the input and be able to predict or forecast [7] mainly by experience based on a predefined set of rules (algorithms). ML was adopted in this study because it is an innovative technology with unique features of flexibility and adaptability that best suit recent technological space [6]. According to [8], various examples of ML algorithms can be integrated into healthcare systems [9,10]. Semi-supervised algorithms are "the partial training set of data is provided" [11,12]. Intelligent IoT-based healthcare systems in educational homes are authentic and emerging. Therefore, researchers are expected to study the field or technology to help improve healthy livelihood among institutional home users and administer educational institutions, countries, and the world to achieve SDGs 3 and 4, which talk about providing quality healthcare and education.

This paper reviews relevant literature on IoT-based EHRs using machine learning, existing health monitoring systems, and resource tools. Again, the study investigates the appropriate methods and techniques needed to implement these systems: the design processes involved, their significant functions, their weaknesses, and the impact on the health environment in Educational Institutions and Elderly Homes. *Figure 1* below depicts the IoT-based EHR environment.

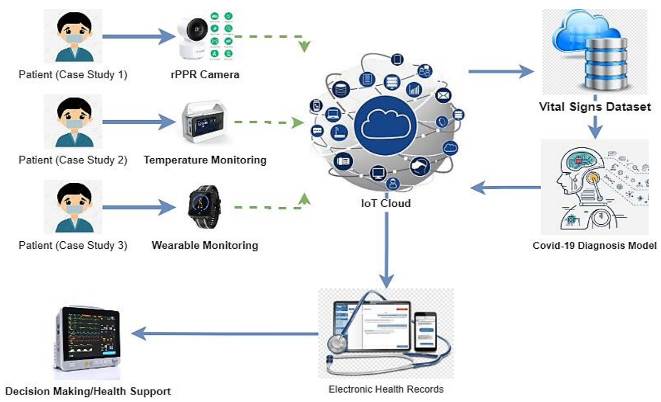

Figure 1. Smart Health Working Environment

An intelligent health environment is any healthcare facility that integrates assets, devices, resources, and tools across its environment to enable real-time data access and analysis to help inform and accelerate patient healthcare delivery processes. According to [13], every smart hospital connects the patients, healthcare professionals, and healthcare institution as a holistic environment that enables seamless integration across technologies such as ML (AI), IoT, 5G network, Software-Defined Networking (SDN), edge routing and storage, and or, cloud computing to improved and secure connectivity at the hospitals and as well for data sharing respectively to aid in the healthcare delivery [14]. In this study, the proposed system implementation is within the residences of students, lecturers, and educational facility users within the institution to help provide holistic healthcare monitoring for the holistic benefit of the users and the academic institutions in general. Given this, the study proposed a data flow diagram for intelligent IoT-based EHRs in a hall of residence, public and private hostels, lecturers' bungalows, institutional hotels, or guest houses. According to [15], IoT has repeatedly transformed our lives in trousers user's attendance, monitoring the ecological temperature with sensors, wireless locks systems, adequate security, smartboard technology, and interactive learning are the main areas applied most. Based on the above, an attempt to monitor the health lives of institutional residence users is being proposed by this study to help improve the lives of institutional residential users. Therefore, this paper reviews the implementation of machine learning algorithms in EHRs systems that use IoT and ML. The study further proposes an intelligent IoT-based EHR system that achieves a better prediction [16] level in a holistic HMS that integrates an EHR system to generate health records, monitor users' health records and health history, predict their health condition, and provide total health security in the institution. The above significance will further enhance the following importance:

- Bring healthcare delivery to users' doorsteps, reduce cost, expenditure, and time spent visiting healthcare facilities by ensuring abnormal health conditions are detected early in institutional residential homes to promote good preventive healthcare delivery among residential users.
- To develop a low-cost and low-maintenance In-Home Health Management System that provides healthcare solutions for homes in Educational Institutions, Elderly Homes, and other institutional homes using Raspberry Pi 4B.
- Provide a real-time intelligent in-home health Management System usage in homes in Educational Institutions, Elderly Homes, and other institutional homes to help eliminate unforeseen health problems.
- To move regular health assessments and other healthcare services, such as monitoring vital statistics of individuals residing in their homes, from an eHealth-focused approach to the Institutional-Home Environment.

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- Contribute to existing knowledge in the field of intelligent IoT-based In-home HMS that deploys EHRs, IoT, and ML.

The contributions mentioned above in this study address the lack of health-predicting systems that deploy recent technologies (IoT, ML, and EHR) within the Educational Institutions and Elderly Homes ecology or other institutional homes to provide an effective telehealth care system for residence users.

2. LITERATURE REVIEW

2.1 Related Work

The EHRs, IoT, and ML are the world's most recent technology for given objects, not computers by definition, computational capabilities, and technological intelligence. The IoT technology describes how entities, also called things, are given computational abilities or powers and hence function like computers. Objects in the IoT ecosystem or environment get these technological powers from the sensors, actuators, and microcontrollers designed to operate on the world's largest network, "The Internet". The Internet of Things (IoT) enables the connectivity of everyday objects (or things) to the Internet by enhancing such devices with identification, sensing, networking, and processing capabilities.
[17–19] concluded that we use IoT in our everyday lives. It is best when automatically providing information on the environment, opening vast possibilities for improving our lives in education, health, industry, banking, etc. Over the last three 3 decades, healthcare systems, applications, and technologies have essentially influenced the healthcare delivery process and affected the health sector unmeasurable [20]. IoT in health has not only improved the data management activities at hospitals, but it has gone a very long way to establish that there can be a contactless diagnosis in the healthcare delivery process, especially in the current time of uncontrollable pandemics invading the world.

ML is an approach to analyzing data, absorbing the dataset to inform a systemic decision. The ML system learns to perform an activity from the pattern instruction (algorithm) and even in the future without necessarily being fed the exact trained data [6,21]. According to [22], machine learning frameworks use data mining detection patterns to match new data point detections, thereby building a predictive model. This predictive model, an algorithm, can ensure massive intelligence in health records management when deployed in EHR systems. Implementing an effective EHR IoT-based system or application requires suitable learning algorithms and domain knowledge in the application area. [23] maintains that supervised, semi-supervised, unsupervised, and reinforcement learning are innovative ML algorithms in healthcare industries.

Even though there is a need to leverage this technology, intelligent health has numerous challenges. Since IoT is over a network, it is prone to intrusion and data insecurity. IoT deployment is a multi-task process [24]; therefore, its implementation requires constant technological monitoring and revision using some effective methods. The proposed system will deploy edge and fog computing to eradicate these challenges. [25] outlined challenges such as scalability, synchronized issues, high-power consumption, Security, and Privacy. Health prediction systems such as [26-32] have contributed significantly to using vital monitoring sensors PPG, Electrocardiogram, and Photoplethysmogram, and IoT boards such as MLX90614 and Raspberry Pi series to implement various health monitoring concepts. One major weakness is the lack of ML algorithms, as most papers set parameters to determine the prediction. The accuracy obtained ranged between 71%-97%, and other metrics that require improvement in the detection process. The cancer detection-related works [46] determine cancerous tissues under microscopic blood or lack machine intelligence in prediction.

2.2 Proposed IoT-based EHR System Using the ML Technology

The proposed IoT-based intelligent EHR system deploys all the arsenals available in IoT and ML to collect vital sign health records using the rPPG sensor, Raspberry Pi Noir camera, and MLX90614 sensor. This essential sign data from the sensors goes through the Raspberry Pi 4B board, the interface with a computer system running the HMS software. In a scenario where the system predicts health status as positive, it sends an SMS for the users to visit a room for a dedicated wearable (watch) to confirm their health status. As part of the system's three [3] factor prediction feature, previous health records of suspected users based on the parameters of vital signs are queried from the institution's health facility's EHRs through an API. The requested data may be records of the previous visits to the institution's health facility or the health records submitted during admissions. These vital sign-recorded data serve as the dataset for the ML algorithms deployed in the system. The basis for querying the potential patient's records from the institution's health facility is to introduce higher data integrity in the proposed system: the form collected by the sensors. The algorithms analyze the EHRs, and a decision (prediction) is made as to whether the user is sick or not (normal or abnormal vital signs). A doctor or specialist is recommended to patients. Based on the severity of the sickness, the student, parent or guardian, and the institutional authority are notified about the illness. These measures ensure holistic healthcare delivery in Educational Institutions and Elderly Homes. Figure 1 below shows the context diagram, which illustrates the interactions between the system and the actors.

2.3 Materials and Resources

Hardware: This proposed system deploys a multi-sensor device at the various entrances of institutional homes. The devices include the following components:

- The Raspberry Pi Noir Camera is an 8MP infrared camera that emits infrared light from the external environment, allowing creative filming and monitoring of health day and night [33].

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- The Raspberry Pi 4B is a powerful, faster, multifunctional microprocessor IoT board that is relatively cheap, reliable, and robust for BACnet and other sensory networks.

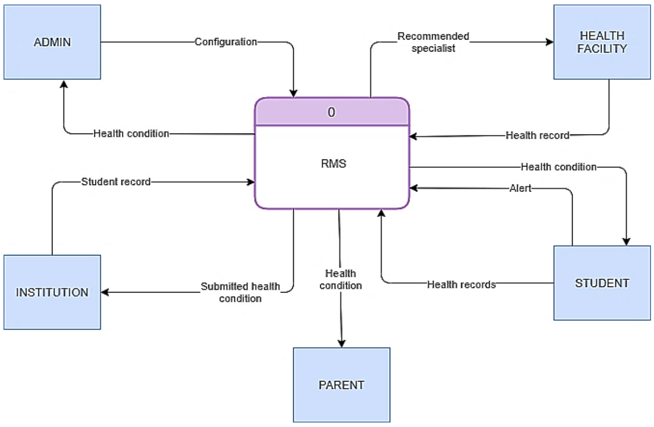

Figure 2. The context diagram of the proposed EHR system

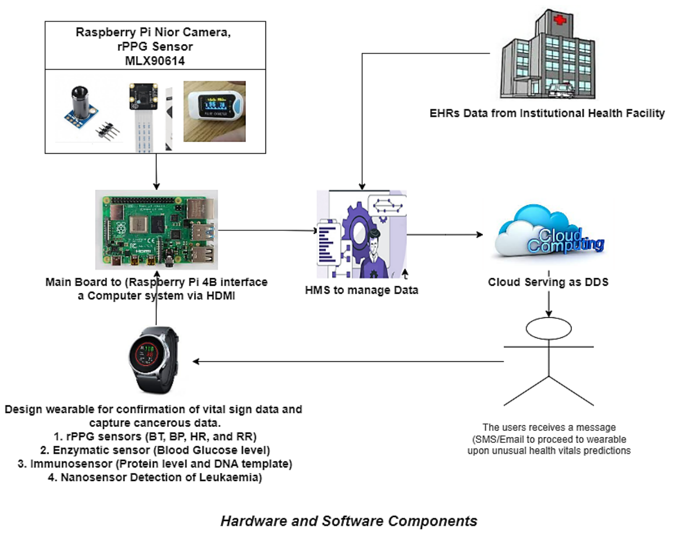

Figure 3. IoT-based EHR in Smart RMS environment

- Remote Photoplethysmography (RPG) is a contactless Face Reader sensor that remotely measures heart rate and rate variability. According to [34], the rPPG requires video recording with high-resolution monitoring of users' physical health and emotions.
- MLX90614ESF is a non-contact body temperature measuring sensor that uses infrared to transmit data to the Raspberry Pi, Arduino. MLX90614 is considered to be effective in building BACnet.
- SAMSUNG Galaxy Watch 4 44mm Smartwatch is proposed as the wearable sensing device in this proposed system. The fundamental basis for integrating the wearable is to help verify the essential health records recorded by IoT sensors.

2.4 Software

The system takes weeks to design a comprehensive HMS that deploys random forest, gradient boosting, or KNN algorithm to predict the health condition of prospective residential users. Python programming language for all the ML deployments. PHP, CSS, JavaScript, and JS.

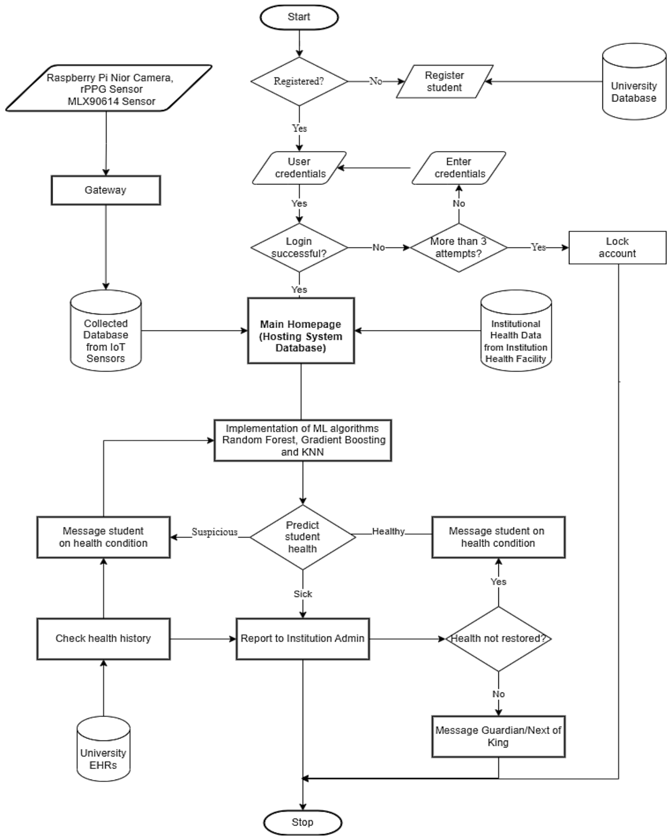

Figure 4a: Data flow Diagram

2.5 System Flow

The proposed intelligent IoT-based EHR system is composed of both hardware and software. The hardware is sensors to be installed at the entrances of the institutional homes. The sensors will capture the passersby's vital signs (Pulse rate, Body temperature, Blood pressure, and Respiratory rate), which are essential for health prediction [35]. For identification purposes, the system also deploys a facial recognition feature to be able to know users. The RF classifier predicts the records captured to determine users' health status, further prompting the positively predicted users to visit a dedicated wearable within the institutional homes and based on the confirmation. The Early Warning Score (EWS) chart implemented in the system will record the values and further evaluation to determine the criticality of the health status for quick and prompt action to revert the aggravating health status, which could lead to death. The criticality level determines if health professionals are to be booked through notification (SMS and e-mail). The central system (HMS) is a desktop system to be installed as an HMS within Educational Institutions and Elderly Homes, and mobile

Apps (Android and iOS) will be made available for users on all the application digital stores. Without credentials, one cannot log in to the system. The figure below shows the flow of the proposed method.

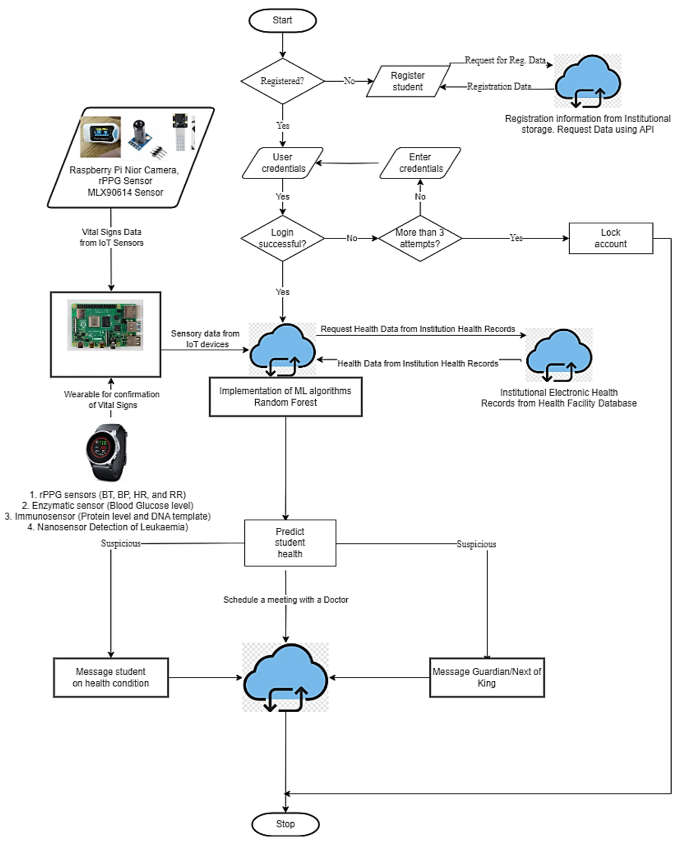

Figure 4b: Data flow Diagram

2.6 IoT in physiological data capturing

Measuring physiological data for health purposes is still rigorously under study by many authors due to limitations or factors hindering the sensing data capturing [36,37]. The physiological data to be captured by the sensing cameras include respiratory rate, blood pressure, temperature, pulse rate, and oxygen saturation (SpO2). Raspberry Pi Nior camera will deploy Shafer's Dichromatic Reflection Model (DRM) optical model technique to measure cardiac signals via photoplethysmography. The Region of Interest (ROI) is selected to determine a trade-off between the absorbed light by the body and the reflection of the emitted electromagnetic waves from the ROI [38]. This is due to the distinct absorption characteristics of oxygenated blood, deoxygenated blood, and skin tissue within the human body. One major challenge confronting measuring physiological changes is individualistic variables such as clothing, hair, and makeup, which makes the measuring process difficult [39]. [40] recommended utilizing visual band (RGB) camera devices, which are much more prevalent than NIR cameras. Suppose the IoT setup recognizes two or more images. The leading IoT challenge to be solved by this study is to optimize the image recording since [40–42] imaging has integrated the facial detection of individuals. In the facial recognition approach, individualistic video recordings will be separated at the level of the frame before the ROI is selected [43,44]. This is because students, by nature, move in groups.

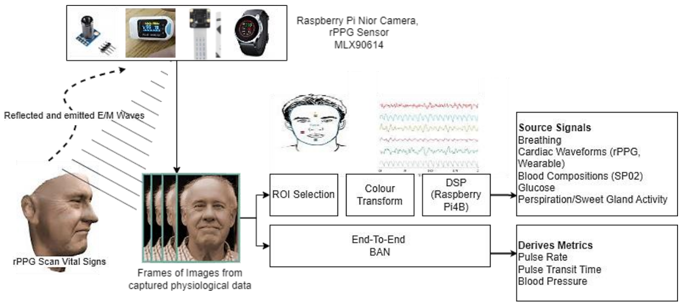

Figure 5: Physiological Image Capturing and the imaging pipeline proposed for the proposed system

An assembled wearable device will comprise an rPPG sensor for vital sign data, an enzymatic sensor for blood glucose level, an immune sensor for protein level, and a DNA template and nano sensor for detecting leukemia. The vital sign health data collected from the UCI health data repository was cleaned to get a dataset of 25219 instances and five attributes. The attributes were assigned variables X and Y variables for training purposes (X=independence variable with the attribute name OUTPUT and Y=dependence variables with the attribute names HR, RESP, Spo2, and TEMP), which are the principal vital signs to be measured for the study. To optimize the performance of the RF algorithm in the Smart in Stu HMS, this study implemented a mathematical derivation below

$$f_{Zit}(x) = \frac{1}{K}\sum_{k=1}^{k} f_i(x), X = 1,2,..N \qquad (1)$$

K represents the based models in an ensemble model, aggregating their result to the meta model in a random forest; the output of the kth base model is denoted by fi(x), with N experiment the dataset's length.

$$f_{WAE}(x) = \sum_{k=1}^{k} w_i f_i(x), X = 1, \ldots..N \qquad (2)$$

Here, K symbolizes the base models, fi(x) signifies the output of the kth base model equal represents the eight of these models in the ensemble model, and N denotes the length of the dataset. The equation employed to determine the model's prediction during training was expressed ones follows: w_i(wi(x) denotes the weight of the kth base model for input x, and N represents the dataset's length. Additionally, Dk(x) signifies the square of the deviation in the prediction of the kth model.

The mHEALTH dataset was imported and run using various classifiers or algorithms [45] in the Jupyter notebook. Table 2 shows the accuracy performance of the trained algorithms, and *figure 6* shows the confusion metrics of the three best algorithms during the dataset training.

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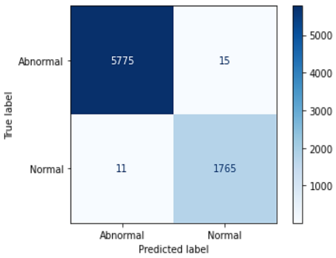
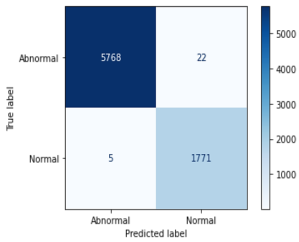
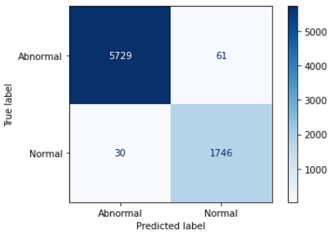


(A: Random Forest)



(B: Gradient Boosting)



(C: K-Nearest Neighbor)

Figure 6: The Confusion Metrics of Best Three Algorithms

From the confusion metrics, the Gradient Boosting classifier is the best-performing model since the False Positive (FP) and True Negative (TN), which are false predictors, are all lower than The Gradient Boosting.

Table 2. Performance results of the best three algorithms using the 80:20 test split

No.	Algorithm	F1-Score	Precision	Recall	Accuracy	Error Rate
1	Random Forest	99.77	99.74	99.80	99.66	0.003
2	The Gradient Boosting	99.76	99.62	99.91	99.64	0.004
3	K-Nearest Neighbor	99.21	98.94	99.48	99.62	0.012

Table 2 shows the three (3) best models that produced significant performance during the training and testing with the dataset. The performance was evaluated using the most common assessment metrics like F1-score, Precision, Recall, and Accuracy, and the respective confusion meters to illustrate the TP, TN, FP, and FN predictions during the model training [46 – 50]. The following formulas were used to calculate the metrics and results for the classifiers.

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

$$Error\ rate = \frac{FP+FN}{TP+FP+FN+TN} \quad (5)$$

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

$$F1\ Score = 2 * \frac{Recall*Precision}{Recall+Precision} \quad (8)$$

4. RESULT AND DISCUSSION

The study experimented with various classification and ensemble algorithms to ascertain which model would better predict performance. From the performance result, the three (3) best-performing algorithms were Random Forest, Gradient Boosting, and K-Nearest Neighbor, justifying ensemble classifiers are very predictive in health predictive systems (51). The random forest classifier recorded an F1-score of 99.77%, the precision of 99.74%, recall of 99.80, the accuracy of 99.66%, and an error rate of 0.0034 (0.34%), followed by the gradient boosting classifier with an F1-score of 99.76%, the precision of 99.62%, recall of 99.91%, accuracy of 99.64% and an error rate of 0.0035 (0.4%) and the K-Nearest Neighbor with an F1-score of 99.21%, precision of 98.94%, recall of 99.48%, accuracy of 99.62% and an error rate of 0.0120 (1.20%) respectively. In comparing the results, the memory of the gradient boosting outperformed the other classifiers, recording 99.91%. The Random Forest significantly performed better in all other measuring metrics used in the study. The classifier had the lowest FN and FP, indicating low false prediction for the respective classes, hence recording the best error rate of 0.0034 (0.34%). Therefore, a holistic comparison shows that the random forest is the best algorithm to be deployed in the proposed IoT-based InsHo HMS to predict the health status of students and other residential students since it produces the highest F1-score, precision, accuracy, and better correct classifying instance prediction thereof, helping to address environmental and health issues [8,37]. Incorrect instances meant that the classifiers had error prediction: if a respondent was predicted to be expected (not sick), the classifier made a mistake by predicting it as Abnormal (ill). The comparison among the three instances indicated that the Random Forest performed better. This makes the Random Tree more effective to be selected for future prediction within the proposed system.

From *table 3*, all the benched mark papers and the state-of-the-art techniques or models have indicated that vital sign data are helpful in training ML models in developing health predictive systems, as indicated by [30]. The model's performance in this study shows a significant improvement in the predictive abilities of the random forest classifier with as high as 99.66% accuracy and 0.34% error rate. By extension, in an instance where the system attempts to predict the health status of 100 students, the proposed system will correctly indicate the health status of 99 students and has the probability of having 7:3 correct predictions on the remaining one person.

Table 3. Performance results of the best three algorithms using the 80:20 test split

Work	Best Methods	F-1 Score	Precision	Recall	Accuracy	Error Rate
[29]	RF	82	-	-	-	-
[32]	Gradient Boosting	92.8	93.2	92.5	94.9	-
[46]	RF	60	52	-	63	-
This Work	RF	99.77	99.74	99.80	99.66	0.003

For predicting wrongly, the proposed system has the slightest chance of predicting wrongly than correctly, with an error rate of 0.003, representing a 0.3% error rate. From Table 3, only [32] had recorded an F1-score of 92.8, precision of 93.2, recall of 92.5, and accuracy of 94.9. From all the results, it is conclusive that the gradient boost classifier performs slightly better than the remaining classifiers and is recommended to be implemented in health predictive systems.

5. CONCLUSION

Residences in educational institutions need more needful preventive healthcare technologies to predict the health status of resident users and bring healthcare delivery services to users' doorsteps, reducing cost and time spent, which leads to poor preventive healthcare delivery in Educational Institutions and Elderly Homes globally proposing a real-time intelligent Home Health Management System to move routine health checks and other healthcare services from healthcare facilities to the institutional home Environment. This helps address the need for health-predicting systems that deploy IoT, ML, and EHR technologies within institutional homes.

IoT-based EHR adaptation in the educational ecology ensures students, teachers, educational administrators, and other educational workers' insecurity in falling sick or dying due to poor pre-detections of ill-health within the academic home or their educational residence is basically due to a lack of essential technologies. IoT and ML technologies are integrated to build smart IoT-based EHRs, which address many of such challenges in smart hospitals but have yet to be attempted in the institutional home where workers or students live as their second homes. A comprehensive review of related literature on IoT for automating EHRs using machine learning algorithms has shown that the lack of IoT-based EHR systems has led to unpredictable illness and death in some circumstances. Specific IoT tools such as Raspberry Pi 4B, Raspberry Pi Noir camera, rPPG sensor, MLX90614, and wearable device (watch) were also assessed for their efficacy in collecting vital sign data of residential users (prospective patients). The study has experimented with a practical model that can enhance health status prediction with critical signs such as blood oxygen level (SpO2), body temperature, and heart rate as variables. Ensemble algorithm techniques such as gradient boosting, random forest, gradient boost, and single algorithms such as KNN, Decision Tree, SVM, and linear regression are coded in Python using Jupyter Notebook. A dataset from the UCI mHEALTH dataset repository was used to train practical ML algorithms to be deployed into the proposed system. The dataset analysis indicated that random forest, gradient boosting, and KNN are the most effective trained models for predicting health within IoT-based EHRs. The RandomForest and gradient boosting algorithms proved to be better models, with an accuracy of 99.66% and 99.64%, respectively. Given this, the study has presented an IoT-based EHR system using an ensemble random forest algorithm to be implemented in educational residences to eliminate unforeseen health conditions and promote effective health prediction and monitoring for the well-being of academic residence users.

6. FUTURE WORK

The scope of this paper includes the design and experimentation of a comprehensive RMS IoT-based EHR framework that can be integrated into existing educational systems globally. Also, an experimental study to prototype low-cost intelligent IoT-based EHRs to be used in all levels of academic institutions is ongoing.

5. ACKNOWLEDGMENTS

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REFERENCES

[1] Keshta I, Odeh A. Security and privacy of electronic health records: Concerns and challenges. Egypt Informatics J [Internet]. 2021;22(2):177–83. Available from: https://doi.org/10.1016/j.eij.2020.07.003
[2] Almutairi A, McCrindle R. Female student nurses attitudes towards electronic medical records in Riyadh City. Int Conf Electr Electron Optim Tech ICEEOT 2016. 2016;2366–70.
[3] Atasoy H, Greenwood BN, McCullough JS. The Digitization of Patient Care: A Review of the Effects of Electronic Health Records on Health Care Quality and Utilization. Annu Rev Public Health. 2019;40:487–500.
[4] Islam MS, Humaira F, Narin Nur DF. Healthcare Applications in IoT. Glob J Med Res. 2020;20(2):11–2.
[5] Ghasempour A. Internet of things in smart grid: Architecture, applications, services, key technologies, and challenges. Inventions. 2019;4(1).
[6] Ford W. Machine Learning for Beginners. A Compr Guide to Algorithms Mach Learn Data Sci. 2017;53(9):1689–99.
[7] Aldahiri A, Alrashed B, Hussain W. Trends in Using IoT with Machine Learning in Health Prediction System. Forecasting. 2021;3(1):181–206.
[8] Jayatilake SMDAC, Ganegoda GU. Involvement of Machine Learning Tools in Healthcare Decision Making. J Healthc Eng. 2021;2021.
[9] Patel W, Patel C, Ramani B, Bhaskar S, Patel M. VitaFALL: NXTGeUH System for Well-Being Monitoring with Fall Recognition and Real-Time Vital Sign Monitoring. Int J Recent Technol Eng. 2020;8(5):5139–45.
[10] Goyal D, Kumar A, Piuri V, Ganzha M. Lecture Notes in Networks and Systems 166 of the Second International Conference on Information Management and Machine Intelligence. 2020.
[11] Gurjit Kaur, Tomar P, Tanque M. Artificial Intelligence to Solve Pervasive Internet of Things Issues. Artificial Intelligence to Solve Pervasive Internet of Things Issues. 2021.
[12] Said AM, Yahyaoui A, Abdellatif T. Efficient anomaly detection for smart hospital IoT systems. Sensors (Switzerland). 2021;21(4):1–24.

[13] Patel WD. Smart Health: Natural Language Processing based Question and Answering Retrieval System in Healthcare. 2019;6(5):1–7.
[14] Harman R. How Is IoT Establishing the Modern Classroom? [Internet]. eLearning Industry. 2019. Available from: https://elearningindustry.com/iot-and-the-modern-classroom-establishing
[15] Patel D. Warish, Chirag P, Patel Monal. Advanced Multi-Threshold Based Reliable Fall Detection System, Recent Advances in Computer Science and Communications. Recent Adv Comput Sci Commun. 2022;15(1):2666.
[16] Tran DN, Nguyen TN, Khanh PCP, Trana DT. An IoT-based Design Using Accelerometers in Animal Behavior Recognition Systems. IEEE Sens J. 2021; XX(XX):1–14.
[17] Nguyen DC, Ding M, Pathirana PN, Seneviratne A, Li J, Niyato D, et al. 6G Internet of Things: A Comprehensive Survey. IEEE Internet Things J. 2022;9(1):359–83.
[18] Nguyen DiC, Cheng P, DIng M, Lopez-Perez D, Pathirana PN, Li J, et al. Enabling AI in Future Wireless Networks: A Data Life Cycle Perspective. IEEE Commun Surv Tutorials. 2021;23(1):553–95.
[19] Chakraborty C, Banerjee A, Garg L, Rodrigues JJPC. Internet of Medical Things for Smart Healthcare [Internet]. Chakraborty C, Banerjee A, Garg L, Rodrigues JJPC, editors. SSRN Electronic Journal. Singapore: Springer Nature Singapore Pte Ltd.; 2020. Available from: https://doi.org/10.1007/978-981-15-8097-0_1
[20] Vaibhavee Jani, Patel W, Shah S. A Theoretical Evaluation of Machine Learning to Predict Enzyme Family. In: International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, 2022, [Internet]. Tuticorin, India: IEEE; 2022. Available from: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9752250&isnumber=97 51722
[21] Taeho Jo. Machine Learning Foundations: Supervised, Unsupervised, and Advanced Learning [Internet]. 2021. 391 p. Available from: https://link.springer.com/book/10.1007%2F978-3-030-65900-4
[22] Tunc MA, Gures E, Shayea I. A Survey on IoT Smart Healthcare: Emerging Technologies, Applications, Challenges, and Future Trends. 2021;1–15. Available from: http://arxiv.org/abs/2109.02042
[23] Anita Gehlot, Rajesh Singh, Praveen Kumar Malik, Lovi Raj Gupta BS. Internet of Things with 8051 and ESP8266. CRC Press; 2021.
[24] Desai F, Chowdhury D, Kaur R, Peeters M, Arya RC, Wander GS, et al. HealthCloud: A system for monitoring the health status of heart patients using machine learning and cloud computing. Internet of Things (Netherlands) [Internet]. 2022;17(December 2021):100485. Available from: https://doi.org/10.1016/j.iot.2021.100485
[25] Pinge A, Bandyopadhyay S, Ghosh S, Sen S. A Comparative Study between ECG-based and PPG-based Heart Rate Monitors for Stress Detection. 2022 14th Int Conf Commun Syst NETworkS, COMSNETS 2022. 2022;84–9.
[26] Sujith AVLN, Sajja GS, Mahalakshmi V, Nuhmani S, Prasanalakshmi B. Systematic review of smart health monitoring using deep learning and Artificial intelligence. Neurosci Informatics [Internet]. 2022;2(3):100028. Available from: https://doi.org/10.1016/j.neuri.2021.100028
[27] Yanamala N, Krishna NH, Hathaway QA, Radhakrishnan A, Sunkara S, Patel H, et al. A vital sign-based prediction algorithm for differentiating COVID-19 versus seasonal influenza in hospitalized patients. npj Digit Med [Internet]. 2021;4(1):1 [29] Pinge A, Bandyopadhyay S, Ghosh S, Sen S. A Comparative Study between ECG-based and PPG-based Heart Rate Monitors for Stress Detection. 2022 14th Int Conf Commun Syst NETworkS, COMSNETS 2022. 2022;84–9.
[28] Nishajith A, Nivedha J, Nair SS, Shaffi JM. Smart Cap – Wearable Visual. 2018 Int Conf Inven Res Comput Appl. 2018;(Icirca):275–8.
[29] Wang W, Brinker AC Den, Haan G De. Single-Element Remote-PPG. 2019;66(7):2032–43.
[30] Patel WD, Pandya S, Koyuncu B, Ramani B, Bhaskar S, Ghayvat H. NXTGeUH: Lorawan based next-generation ubiquitous healthcare system for vital signs monitoring. 2018 Conf Inf Commun Technol CICT 2018. 2018;1–8.
[31] Allado E, Poussel M, Moussu A, Saunier V, Bernard Y, Albuisson E, et al. Innovative measurement of routine physiological variables (heart rate, respiratory rate, and oxygen saturation) using a remote photoplethysmography imaging system: A prospective comparative trial protocol. BMJ Open. 2021;11(8).
[32] Ramani B, Patel W, Solanki K. Stress Ocare: An advanced IoMT-based physiological data analysis for anxiety status prediction using cloud computing. J Discret Math Sci Cryptogr. 2022;25(4):1019–29.
[33] Ramani B, Patel W, Solanki K, Patel M. An Energy-Efficient Stress Monitoring System Using Physiological Data. Int J Eng Res Technol. 2021;9(8):132–7.
[34] Molinaro N, Schena E, Silvestri S, Bonotti F, Aguzzi D, Viola E, et al. Contactless Vital Signs Monitoring from Videos Recorded With Digital Cameras: An Overview. Front Physiol. 2022;13(February).
[35] Wang Y, Wang W, Zhou M, Ren A, Tian Z. Remote monitoring of human vital signs based on 77-GHZ MM-WAVE FMCW radar. Sensors (Switzerland). 2020;20(10).
[36] Mudnur SP, Raj Goyal S, Jariwala KN, Patel WD, Ramani B. Hiding the Secret Image Using Two Cover Images for Enhancing the Robustness of the Stego Image Using Haar DWT and LSB Techniques. 2018 Conf Inf Commun Technol CICT 2018. 2018;(2):1–4.
[37] Maxime Konan DA, Patel W. I-NXGeVita: IoMT based ubiquitous health monitoring system using deep neural networks. 2018 3rd IEEE Int Conf Recent Trends Electron Inf Commun Technol RTEICT 2018 - Proc. 2018;552–7.
[38] Manic KS, Biju R, Patel W, Khan MA, Raja NSM, Uma S. Extraction and Evaluation of Corpus Callosum from 2D Brain MRI Slice: A Study with Cuckoo Search Algorithm. Comput Math Methods Med. 2021;2021.
[39] Abdulkareem KH, Mohammed MA, Salim A, Arif M, Geman O, Gupta D, et al. Realizing an Effective COVID-19 Diagnosis System Based on Machine Learning and IoT in Smart Hospital Environment. IEEE Internet Things J. 2021;8(21):15919–28.
[40] Kangra K, Singh J. Comparative analysis of predictive machine learning algorithms for diabetes mellitus. Bull Electr Eng Informatics. 2023;12(3):1728–37.
[41] Sankaravadivel V, Thalavaipillai S, Rajeswar S, Ramalingam P. Feature-based analysis of endometriosis using machine learning. Indones J Electr Eng Comput Sci. 2023;29(3):1700–7.
[42] Kurniawan R, Supardi J, Mohamad FS. A Framework for Determining the Big Five Personality Traits Using Machine Learning Classification through Graphology. 2023;2023.
[43] Beltran H, Sansano E, Pecht M. Machine learning techniques suitability to estimate the retained capacity in lithium-ion batteries from partial charge/discharge curves. J Energy Storage [Internet]. 2023;59(September 2022):106346. Available from: https://linkinghub.elsevier.com/retrieve/pii/S2352152X22023350
[44] Ramon J, Palacios-marqués D, Ribeiro-Soriano D. Using data mining techniques to explore security issues in smart living environments in Twitter. Comput Commun [Internet]. 2021;179(August):285–95. Available from: https://doi.org/10.1016/j.comcom.2021.08.021
[45] Ghaderzadeh M, Asadi F, Hosseini A, Bashash D, Abolghasemi H, Roshanpour A. Machine Learning in Detection and Classification of Leukemia Using Smear Blood Images: A Systematic Review. Vol. 2021, Scientific Programming. Hindawi Limited; 2021.
[46] Rehman O, Farrukh Z, Al-Busaidi AM, Oman M, Cha K, Park SJ, et al. IoT Powered Cancer Obs Kothari, Aansi A., et al. "A novel approach towards context-based recommendations using support vector machine methodology." Procedia Computer Science 57 (2015): 1171-1178. Elsevier.
[47] Kothari, Aansi A., et al. "A novel approach towards context-sensitive recommendations based on machine learning methodology." 2015 Fifth International Conference on Communication Systems and Network Technologies. IEEE, 2015.