International Journal of Data Science and Artificial Intelligence (IJDSAI)
Volume 3, Issue 4, July – August (2025)

RESEARCH ARTICLE

REG NET BASED PATIENT HEALTH MONITORING AND CLASSIFICATION SYSTEM USING IOT SENSORS AND SECURE DATA PROCESSING

R. Pradeebha [1, *] and A. Ahilan [2]

[1] Assistant Professor, Department of Computer Science and Engineering, Cape Institute of Technology, Levengipuram, Anjugramam, Rajakrishnapuram, Tamil Nadu, India
[2] Associate Professor, Department of Electronics and Communication Engineering, PSN College of Engineering and Technology, Tirunelveli, Tamil Nadu, India.
[*]*Corresponding e-mail: pradeebha1991@gmail.com*

Abstract – Patient health monitoring refers to the application of technology in the process of constant monitoring and analysis of essential signs and health rates of a patient, which will provide the opportunity to identify problems early, manage chronic diseases more efficiently, and receive timely treatments. This can be done remotely with the help of smartwatches or fitness trackers, or in person with the help of medical equipment. To address these issues, this paper proposed a novel patient health monitoring. First, a smart patient health monitoring system that gathers vital health parameters that including blood sugar, heart rate monitors, temperature sensors, and smartphone applications. The pre-processing of data which includes data normalization, data tokenization and data cleaning procedures are performed to transform the data so that it is more accurate and reliable. DL-based classification model refers to the analysis of the processed data to ascertain the health of patients as either abnormal or normal. The system sends an alert on the smartphone of the patient in the case of abnormal conditions to initiate a quick responding action. In addition to this, patient data safety is guaranteed through authentication system, where users can log in to this system with the assistance of secure login credentials. The practice will allow an extended observation of health, detection of any medical anomaly, and treatment; therefore, improve the management of patients and reduce risks to healthcare.

Keywords *– Patient Health Monitoring, Deep Learning, Reg Net, Normal, Abnormal.*

1. INTRODUCTION

The patient health monitoring system is a technology that measures and monitors vital signs and health information of a patient which can be monitored and intervened remotely by enhancing the medical and medical care of the patient [1]. Patient health monitoring system is an advantageous technological solution to healthcare by which a medical staff can be capable to monitor the measures of health of a patient remotely or in real time [2]. Using these systems, information regarding the vital signs such as heart rate, blood pressure and temperature, and oxygen saturation among others is typically collected with the help of sensors [3]. This data is collected and these are forwarded into the central system to be interpreted and processed. The IoT networking system with the deep learning technology has redesigned the programming of the home medical system to enable remote check-ups and the detection of illnesses at the early stage [4]. IoT technology allows the collection of huge amounts of physiological data using wearable technology or sensors, including saturation of oxygen in the blood, heart rate, body temperature, and ECG data [5]. This collected data is uploaded to a remote server to undergo deep learning algorithms to identify the trends of multiple health risks [6]. Deep learning algorithms are capable of handling large volumes of data and learning independently to find significant patterns that portray some medical conditions.

The authentication measures that come in the system require the user to present valid credentials before gaining access to the health information in the system to protect the security and privacy of patient information [7]. The incorporation of smartphone applications enhances patient care and facilitates early sickness detection by enabling patients and medical professionals to remotely examine health information in real time [8]. Healthcare Security refers to a system of safeguards designed to protect physical property and ensure safety for individuals within healthcare facilities, aiming to reduce the likelihood of harmful incidents and minimize their impact by continuously evaluating and adapting security measures [9,10]. The major contribution of the work has been followed by

- Initially, data collect from various sensors namely smartwatch, heart rate monitoring, temperature sensor, and smart phone application.

- Pre-processed using normalization, Tokenization and Data cleaning to reduce noise.
- Reg net for classification has been classified into two types namely normal and abnormal.

The remaining portion of the work has been followed by, section 2 depicts the literature review, section 3 illustrates the proposed methodology, section 4 denotes the result and discussion and section 5 depicts the conclusion and future work of the proposed methodology.

2. LITERATURE REVIEW

In 2022 Thilagam, K., et al., [16] presented a deep learning privacy and data analytics solution based on the Internet of Things. The user's data is gathered, and private information is kept safe and secure. A convolutional neural network (CNN) that excludes user personal information is used to evaluate health-related data in the cloud. Experimental investigation demonstrates that the proposed strategy is durable and successful in terms of little privacy leakage and excellent data integrity.

In 2021 Verma, A., et al., [17] developed a unique GFI-GWALO hybrid classifier was presented for risk prediction and severity analysis. The suggested approach securely stored the data and accurately categorized the disorders. As a result, it achieved 100 percent accuracy. As a result, the suggested approach obtained zero error, 99% F-measure, 99.98% specificity, and a 99.50% accuracy rate.

In 2021 Christo, M.S., et al [18] suggested an elliptic curve cryptography (ECC) to share the data efficiently. The suggested system will be based on data authentication, ensuring 512-bit encryption, and Blockchain that will provide confidentiality to the ethical user. Encrypted data is also stored on edge components to enable quick access whereas authenticated users can decrypt, process and store updated data on the Blockchain and the cloud server. The proposed model increases the protection of medical data. via edge devices; it can however face the problems of computational overhead and limited resources.

In 2021 Abdellatif, A.A., et al [19] presented a blockchain framework of Medge-chain computing in healthcare security. The proposed design proposes the use of blockchain technology to store the records of the transfer of user data and manage the amount of blockchain transactions. to guarantee data security. User centricity is achieved by enabling consumers to have a eye on their data transactions. The proposed model increases the effectiveness of medical data sharing. Nonetheless, it can have problems with interoperability.

In 2022 Azbeg, K., et al., [20] recommended BlockMedCare, an IoT and blockchain-based safe healthcare solution. The technology is designed to make remote patient monitoring easier, especially for long-term diseases that need to be checked often. Using the re-encryption proxy in combination with Blockchain to store hash data ensures security. Access is managed by smart contracts. When compared to traditional methods, the experimental system demonstrated a notable improvement in healthcare security.

In 2022 Ali, A., et al., [21] Created a unique deep-learning-based safe search-able blockchain as a distributed database that uses homomorphic encryption to allow users to securely access data via search. The hyperledger tool uses smart contracts to implement the recommended algorithms. The proposed approach is assessed in contrast to current ones. Our proposed solution considerably increases security, anonymity, and user behavior tracking, resulting in a more efficient blockchain-based IoT system when compared to existing models.

In 2021 Anand, A., et al., [22] presented a novel DL model (CNN-DMA) based on a CNN classifier to identify malware threats. The initial convolutional layer takes a 32 × 32 × 1 input picture. Results are obtained from the Malimg dataset, which contains 25 malware families, and our model has discovered malware. The suggested CNN-DMA model is 99 percent accurate and has been verified using cutting-edge methodologies.

In 2021 Butt, U.M., et al., [23] offered an approach to diabetes classification, early diagnosis, and prediction based on machine learning. Additionally, it outlines a potential Internet of Things (IoT)-based diabetic monitoring device that allows a healthy individual with the disease to check his blood glucose (BG) level. The experimental evaluation is performed on a benchmark PIMA Indian Diabetes dataset.

In 2022 Ali, A., et al., [24] proposed a novel hybrid deep neural network-based binary spring search (BSS) model based on group theory (GT). The proposed method detects intrusions within the Internet of Things network. Consequently, our proposed approach is cost-effective and improves security, efficiency, and transparency. For research and evaluation, we used OrigionLab and Hyperledger Fabric, two blockchain-based technologies, to run our simulations.

In 2021 Kishor, A., et al., [25] proposed an Intelligent Multimedia Data Segregation (IMDS) approach that separates multimedia data from the machine learning model used to determine the overall latency in fog computing environments. By using the simulated findings, we were able to increase the quality of services in e-healthcare, reduce latency by around 95%, and reach 92% classification accuracy.

3. PROPOSED METHODOLOGY

In this section a novel has been proposed. Initially, data collect from various sensors namely smartwatch, heart rate monitoring, temperature sensor, and smart phone application. Then data can be pre-processed using normalization, Tokenization and Data cleaning to reduce noise. After the pre-processed data can be sent to Reg net for classification has been classified into two types namely normal and abnormal. If the system detects abnormal health conditions, it triggers an alert via the patient's smartphone. Figure 1depicts the proposed methodology

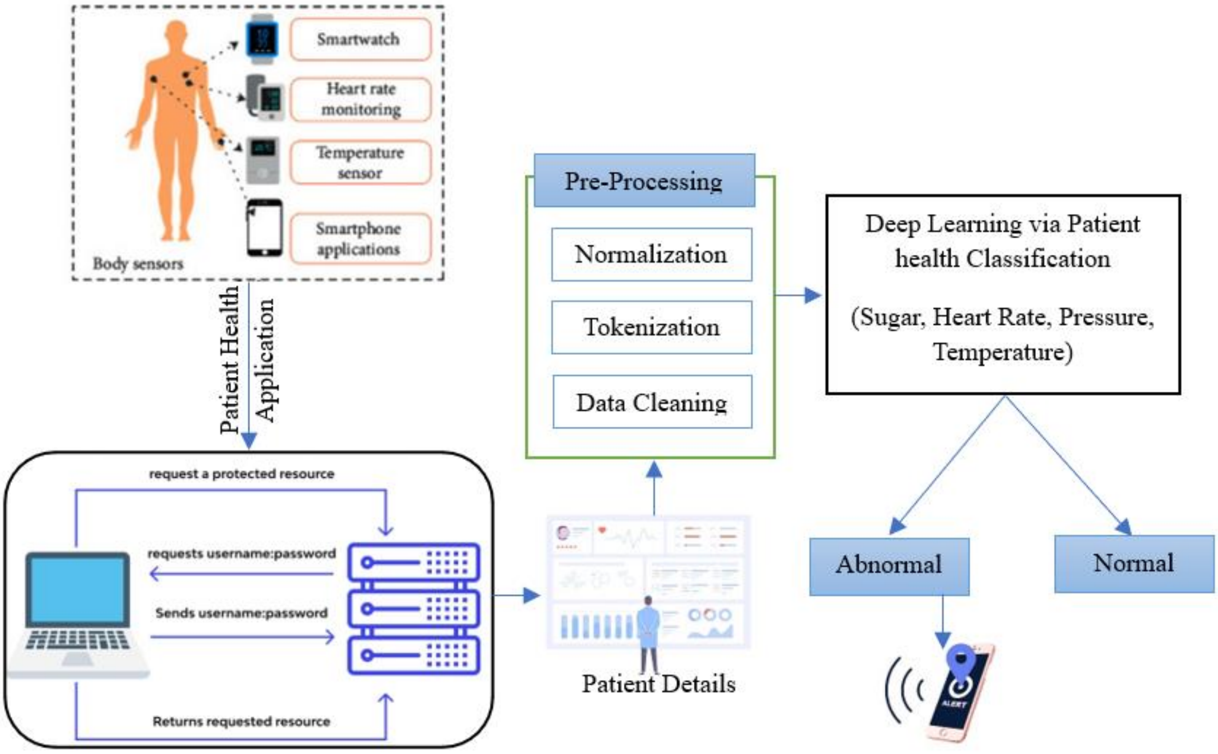

Figure 1. Proposed Methodology

3.1. Tetra Sensor

3.1.1. Smart Watch

Patients can monitor their health remotely with a smartwatch. It provides data to caregivers or healthcare providers and continuously monitors critical health factors. Emergency response, chronic disease management, and early disease detection are all aided by this. Smartwatches can give patients with diabetes, hypertension, or heart disease real-time health updates, which can cut down on the frequency of hospital stays.

3.1.2. Heart rate monitoring

Smartwatches with heart rate monitoring are essential for patient care because they offer continuous cardiac monitoring, which is advantageous for a number of patient populations. It assists in identifying arrhythmia, bradycardia, or tachycardia in cardiac patients, allowing for early intervention. Heart rate variations linked to high blood pressure can be tracked by hypertension patients, and heart rate patterns throughout recovery are beneficial for post-surgery patients. Smartwatches also notify caregivers of aberrant heart rates in the elderly, lowering the risk of unexpected cardiac crises and guaranteeing prompt medical intervention.

3.1.3. Temperature Sensor

A smartwatch with a temperature sensor can track the temperature of a patient and identify an abnormal change in temperature that can be applied in most healthcare situations. It helps in the detection of fever, identification of infections or early symptoms of an illness, and can be used to track COVID-19 and flu tracking body temperature variations to identify symptoms of fever. It gives physicians knowledge on whether a patient has or not. Postoperative temperature increases, which is a pointer to the possibility of infection. It is also useful in the health of women as it helps in the monitoring of the menstrual cycle through basal body temperature and this offers critical information to the reproductive health system.

3.1.4. Smart Phone application

A mobile phone application gathers and processes data of wristwatch to enable effective patient care. It allows physicians to cost-effectively pay remote attention to the health of patients as it provides real-time and historic data in order to obtain a better diagnosis and treatment planning. Patients have the ability to track their vitals, including heart rate, temperature, or oxygen levels and activity records. The app also includes automatic notifications and alarms, notifying physicians or caregivers of dangerous conditions, such as irregular heart rate, severe fever or falls. It can also offer medication reminders to assist chronic patients to take their medicines on schedule and integration to telemedicine platforms enabling the easy sharing of health records during virtual consultations.

3.2. Pre-processing via NTD

Data normalization as applied in databases is the act of arranging data into tables and establishing a relationship among tables based on predefined rules to reduce redundancy and improve data integrity. The process of converting a physical object into a digital one is called tokenization. Also, it is possible to analyze big amounts of data quickly through tokenization. or to protect sensitive data. Finding and correcting errors, inconsistencies, and inaccuracies in datasets to improve their reliability, quality, and accuracy for analysis or other applications is known as data cleaning, often called data cleansing or data scrubbing.

3.3. CNN based patient Health Classification

RegNet is a method for repeatedly exploring and creating neural network topologies that assumes accountability for the relationships between framework functionality, normalization techniques, and structural choices. A 1*1 conv2d, a 3*3 group conv2d, a final 1*1 conv2d, and a ReLU layer after each conv2d level make up each unit. The convolution layer is followed by the pooling layer. Usually, the pooling procedure is used inside the generated feature networks to minimize the overall number of characteristic representations and network configurations through the use of the relevant calculations. The stride (s=1) maximum pooling was used in this study. As a result, the numbers were 128, 64, and 32. The framework's maximum input size is 224x224, which is the typical RegNet system data size. The suggested architecture has nine convolutional 2D layers, flatten level, and dense layers with filter sizes of 128* 64* 32. Training variables for 224x224 drawings total 194*903*073.

The normalized linear process that determined the RegNet framework's architecture was impacted by selected parameters rather than fixed variables like width and length. Equation (1) was optimized, and the unit widths were found using the following formula.

$$S_k = \omega_0 + \omega_c . k \;\; for \; 0 \leq k \leq l \qquad (1)$$

The breadth of each block was increased by a number of ω_a with each new block. An additional variable ω_0, was subsequently added in the estimation, and the result was S_k. The RegNet module may be characterized as follows:

$$\omega_k = \omega_0 . \omega_n{}^{rk} \qquad (2)$$

After calculating the encoded per-block dimensions and scaling rk, the normalized S_k is given by equation (2). Each phase's width, j, was efficiently determined by summing all of the units of the same size that were used to create each phase. The variable at width W, ω_0, indicates the initial phase, ω_c, the gradient, and ω_n, the variable dimension, are used to define the RegNet region of design and create a RegNet.

4. RESULT AND DISCUSSION

The efficiency of the proposed technique is computed with the help of MATLAB 2019b. The analysis of the performance is made on the basis of several computational values, such as recall, precision, mean squared error (MSE), accuracy, and F1-score. The experiment has been conducted on a computer having an Intel i9-9820X 3.30GHz processor, 2TB of RAM, and running on Ubuntu 20.04.1 LTS. The performance of the proposed model is compared to CNN-DMA, IMDS and GPI-GWALO respectively.

Figure 2 demonstrates the heart rate (BPM) of four people in three states: Rest, Normal and Walking. The colors are denoting the various activity levels, which are Rest in purple, Normal in yellow, and Walking in brown. The data reveal that the heart rate goes up as one engages in more physical activity with the lowest being when the body has rested, moderate where normal activity is concerned, and the highest when walking is involved. Error bars indicate small levels of deviations in measurements. The trend is familiar to all people, which proves the desired physiological reaction to the growth of physical activity.

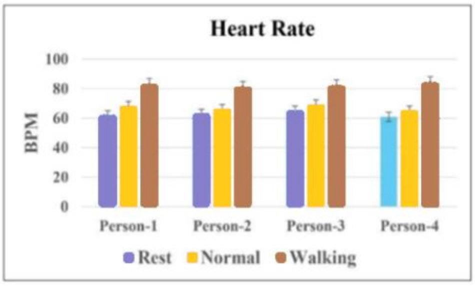

Figure 2. Performance analysis of Heart Rate

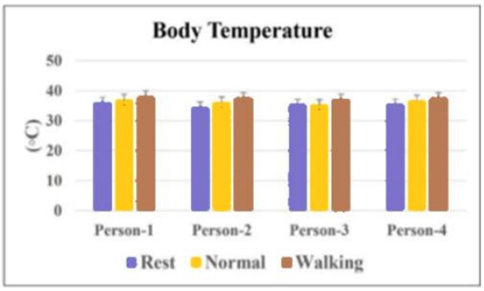

Figure 3. Performance analysis of Body Temperature

Figure 3 illustrates the body temperature (in degC) in four people at three conditions, namely, Rest (purple), Normal (yellow) and Walking (brown). The data show that the body temperature changes are not significant, and at most, there are minor differences in the temperature between the activities of different levels. Walking, Rest and Normal share the differences between their temperatures but these are relatively insignificant. The use of error bars implies some small fluctuations in the measurements. This tendency causes the belief that physical activity does not affect the body temperature too significantly and in a controlled range.

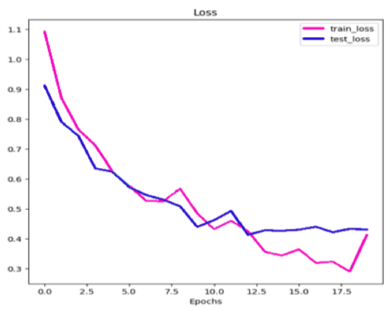

Figure 4. Loss curve of the proposed method

Figure 4 shows the training and testing loss curves in 20 epochs, which shows the quality at which the model is learning. It can be said that both curves decline gradually, which implies effective training. The error of the train and test values is near each other, suggesting that the model is generalized and it is not overfitting. The gradual changes in the curves are acceptable though the overall downward trend is always constant which demonstrates the fact that the model works better with time. The loss values are not high after all, and this is a good indicator of convergence.

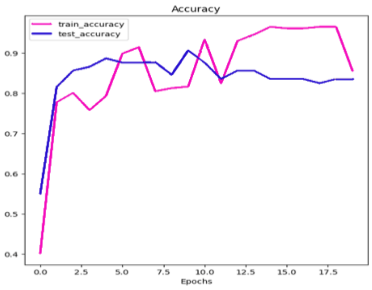

Figure 5. Accuracy curve of the proposed method

Figure 5 will show the training accuracy curve, testing accuracy curve in 20 epochs. The two curves are steep during the early epochs signifying a swift learning process. The accuracy in training keeps increasing to above 0.9, whereas the accuracy in testing reaches the range of 0.85 to 0.9. This slight gap suggests minor overfitting, but the model generalizes well overall. The fluctuations in accuracy are common, especially in smaller datasets or complex models.

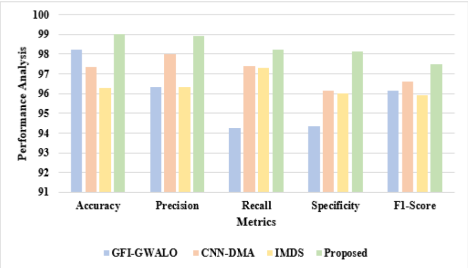

Figure 6. Performance Analysis

Figure 6 shows the performance of the proposed method, CNN-DMA, IMDS, and GFI-GWALO across five assessment metrics: F1-Score, Accuracy, Precision, Recall, and Specificity. 99% Accuracy, Precision, and Recall, 98% Specificity, and F1-Score are all criteria that the proposed model routinely exceeds the other three models on. In close pursuit is CNN-DMA, which has an F1-Score of 97%, Accuracy 97.5%, Precision 98%, Recall 97.5%, and Specificity 96%. The performance of IMDS is somewhat worse, with an F1-Score of 96%, Accuracy 96%, Precision 96.5%, Recall 97%, and Specificity 95.5%. The performance of GFI-GWALO is the lowest, with an F1-Score of 96%, Accuracy of about 98%, Precision of 96%, Recall of 94%, and Specificity of 94%.

5. CONCLUSION

In this section a novel has been proposed. In this paper a novel has been proposed for patient health monitoring. Initially, a smart patient health monitoring system that collects vital health parameters such as blood sugar, heart rate, blood pressure, and body temperature using wearable devices. The collected data undergoes pre-processing, including normalization, tokenization, and data cleaning, to enhance accuracy and reliability. A Reg net-based classification model analyzes the processed data to categorize patient health status as either normal or abnormal. When abnormal conditions occur, the system sends an alert message on the smartphone of the patient to take immediate action. Also, the security of patient information is performed with the help of an authentication component that checks the access by using valid log-in credentials. The approach assists in sustaining ongoing health care and detecting preventive medical anomalies and responding to them in time, thus promoting patient care and reducing the risks to the healthcare segment.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

FUNDING STATEMENT

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors

ACKNOWLEDGEMENTS

The author would like to express his heartfelt gratitude to the supervisor for his guidance and unwavering support during this research for his guidance and support.

REFERENCES

[1] G. O. Young, "Synthetic structure of industrial plastics (Journal Article)", *Plastics*, vol. 3, no. 2, pp. 15–64, 1964. [CrossRef] [Google Scholar] [Publisher Link]

[2] G. O. Young, Synthetic structure of industrial plastics (Book style with paper title and editor), in *Plastics*, 2nd ed. vol. 3, J. Peters, Ed. New York: McGraw-Hill, 1964, 15–64. [CrossRef] [Google Scholar] [Publisher Link]

[3] G. O. Young, "Synthetic structure of industrial plastics (Conference Proceedings)," International conference on ACIDS 2020, Phuket, Thailand, March 23-26, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[4] B.M. Mahmmod, M.A. Naser, A.H.S. Al-Sudani, M. Alsabah, H.J. Mohammed, H. Alaskar, F. Almarshad, A. Hussain, and S.H. Abdulhussain, "Patient monitoring system based on internet of things: A review and related challenges with open research issues," *IEEE Access*, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] P. Bhambri, and A. Khang, "Managing and monitoring patient's healthcare using AI and IoT technologies," In *Driving Smart Medical Diagnosis Through AI-Powered Technologies and Applications*, pp. 1-23, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[6] S. Kanakaprabha, G.G. Kumar, B.P. Reddy, Y.R. Raju, and P.C.M. Rai, "Wearable Devices and Health Monitoring: Big Data and AI for Remote Patient Care," *Intelligent Data Analytics for Bioinformatics and Biomedical Systems*, pp. 291-311, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[7] S. Arun, E.R. Sykes, and S. Tanbeer, "RemoteHealthConnect: Innovating patient monitoring with wearable technology and custom visualization," *Digital Health*, vol. 10, pp. 20552076241300748, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[8] A. Sharma, D.B. Pesarlanka, and S. Sharma, "Integrating Machine Learning, Artificial Intelligence, Deep Learning, and IoT in Remote Patient Monitoring," In *Future Innovations in the Convergence of AI and Internet of Things in Medicine*, pp. 285-318, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[9] M.I. Yaqoob Akbar, "Leveraging Edge AI and IoT for Remote Healthcare: A Novel Framework for Real-Time Diagnosis and Disease Prediction," 2025. [CrossRef] [Google Scholar] [Publisher Link]

[10] D. Rangarajan, A. Rangarajan, C.K.K. Reddy, and S. Doss, "Exploring the Next-Gen Transformations in Healthcare Through the Impact of AI and IoT," In *Intelligent Systems and IoT Applications in Clinical Health*, pp. 73-98, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[11] M. Anjum, N. Kraiem, H. Min, A.K. Dutta, Y.I. Daradkeh, and S. Shahab, "Opportunistic access control scheme for enhancing IoT-enabled healthcare security using blockchain and machine learning," *Scientific Reports*, vol. 15, no. 1, pp. 7589, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[12] D. Zeng, A. Badshah, S. Tu, M. Waqas, and Z. Han, "A Security-Enhanced Ultra-Lightweight and Anonymous User A Security-Enhanced Ultra-Lightweight and Anonymous User Authentication Protocol for Telehealthcare Information Systems," *IEEE Transactions on Mobile Computing*, no. 01, pp. 1-13, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[13] G. Kothai, P. Harish, D. Ajinesh, and V. Sathyanarayanan, "Optimizing Data Privacy and Scalability in Health Monitoring: Leveraging, Encryption, Blockchain, and Cloud Technologies," In *Critical Phishing Defense Strategies and Digital Asset Protection*, pp. 245-270, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[14] K. Thilagam, A. Beno, M.V. Lakshmi, C.B. Wilfred, S.M. George, M. Karthikeyan, V. Peroumal, C. Ramesh, and P. Karunakaran, "Secure IoT Healthcare Architecture with Deep Learning-Based Access Control System," *Journal of Nanomaterials*, vol. 2022, no. 1, pp. 2638613, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[15] A. Verma, G. Agarwal, A.K. Gupta, and M. Sain, "Novel hybrid intelligent secure cloud internet of things based disease prediction and diagnosis," *Electronics*, vol. 10, no. 23, pp. 3013, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[16] M.S. Christo, V.E. Jesi, U. Priyadarsini, V. Anbarasu, H. Venugopal, and M. Karuppiah, "Ensuring improved security in medical data using ecc and blockchain technology with edge devices," *Security and Communication Networks*, vol. 2021, no. 1, pp. 6966206, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[17] A.A. Abdellatif, L. Samara, A. Mohamed, A. Erbad, C.F. Chiasserini, M. Guizani, M.D. O'Connor, and J. Laughton, "Medge-chain: Leveraging edge computing and blockchain for efficient medical data exchange," *IEEE Internet of Things Journal*, vol. 8, no. 21, pp. 15762-15775, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[18] K. Azbeg, O. Ouchetto, and S.J. Andaloussi, BlockMedCare: A healthcare system based on IoT, Blockchain and IPFS for data management security. *Egyptian informatics journal*, vol. 23, no. 2, pp. 329-343, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[19] A. Ali, M.F. P asha, J. Ali, O.H. Fang, M. Masud, A.D. Jurcut, and M.A. Alzain, "Deep learning based homomorphic secure search-able encryption for keyword search in blockchain healthcare system: A novel approach to cryptography," *Sensors*, vol. 22, no. 2, pp. 528, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[20] A. Anand, S. Rani, D. Anand, H.M. Aljahdali, and D. Kerr, "An efficient CNN-based deep learning model to detect malware attacks (CNN-DMA) in 5G-IoT healthcare applications," *Sensors*, vol. 21, no. 19, pp. 6346, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[21] U.M. Butt, S. Letchmunan, M. Ali, F.H. Hassan, A. Baqir, and H.H.R. Sherazi, "Machine learning based diabetes classification and prediction for healthcare applications," *Journal of healthcare engineering*, vol. 2021, no. 1, pp. 9930985, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[22] A. Ali, M.A. Almaiah, F. Hajjej, M.F. Pasha, O.H. Fang, R. Khan, J. Teo, and M. Zakarya, "An industrial IoT-based blockchain-enabled secure searchable encryption approach for healthcare systems using neural network," *Sensors*, vol. 22, no. 2, pp. 572, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[23] A. Kishor, C. Chakraborty, and W. Jeberson, "A novel fog computing approach for minimization of latency in healthcare using machine learning," *IJIMAI*, vol. 6, no. 7, pp. 7-17, 2021. [CrossRef] [Google Scholar] [Publisher Link]

AUTHORS

R. Pradeebha is currently serving as an Assistant Professor in the Department of Computer Science and Engineering at Cape Institute of Technology, where she has been contributing since December 2022. With a strong commitment to academic excellence and student development, she is actively involved in planning and delivering lectures, designing course materials, and ensuring effective coverage of the university syllabus. Her teaching approach emphasizes exploration-based learning, encouraging students to engage in discovery-driven projects that enhance their technical and analytical skills. In addition to her teaching responsibilities, she is dedicated to academic research and regularly prepares proposals and contributes scholarly articles to reputed journals. Her professional interests include curriculum innovation, research in emerging areas of computer science, and fostering student-centered learning environments.

Ahilan A. received Ph.D. from Anna University, India, and working as an Associate Professor in the Department of Electronics and Communication Engineering at PSN College of Engineering and Technology, India. His area of interest includes FPGA prototyping, Computer vision, the Internet of Things, Cloud Computing in Medical, biometrics, and automation applications. Served Guest editor in several journals of Elsevier, Benthom, IGI publishers. Also, have contributed original research articles in IEEE Transactions, SCI, SCIE, and Scopus indexed peer-review journals. He presented various international conference events like ASQED (Malaysia), ESREF (France). He is doing as a reviewer in IEEE Industrial Informatics, IEEE Access, Measurement, Multimedia Tools & Applications, Computer Networks, Medical systems, Computer & Electrical Engineering, neural computing and applications, Cluster Computing, IET Image Processing, and so on. He has IEEE and ISTE membership. He has worked as a Research Consultant at TCS, Bangalore, where he has guided many computer vision projects and Bluetooth Low Energy projects. Hands on programming in MATLAB, Verilog and python at various technical institutions around India.

Arrived: 16.07.2025

Accepted: 21.08.2025