Indonesian Journal of Electrical Engineering and Computer Science
Vol. 39, No. 2, August 2025, pp. 1155~1163
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v39.i2.pp1155-1163

IoT-enabled smart healthcare system with machine learning for real-time vital sign monitoring and anomaly detection

Sanjay Deshmukh, Shrey Shah, Asim Wahedna, Nimish Sabnis
Department of Electronics and Telecommunication, D.J. Sanghvi College of Engineering, Mumbai, Maharashtra, India

Article Info

Article history:

Received Dec 17, 2024
Revised Mar 23, 2025
Accepted Jul 2, 2025

Keywords:

Anomaly detection
Healthcare monitoring
Internet of things
Machine learning
Vital signs

ABSTRACT

This paper presents an innovative IoT-enabled smart healthcare system that combines real-time vital sign monitoring with machine learning-based anomaly detection. The system utilizes a MAX30102 photoplethysmography sensor interfaced with an ESP-32 microcontroller to collect heart rate and blood oxygen saturation (SpO2) data. MQTT protocol ensures efficient data transmission to a cloud database. A long short-term memory (LSTM) neural network architecture is employed for time-series prediction of vital signs and anomaly detection. The system demonstrates high accuracy, with mean squared errors of 0.3% in offline testing and over 90% accuracy in real-time prediction. This affordable and scalable solution offers continuous monitoring capabilities, making it viable for widespread adoption in healthcare settings. The integration of IoT and machine learning techniques provides a robust framework for early detection of health anomalies, potentially improving patient care and outcomes in various medical scenarios.

Corresponding Author:

Sanjay Deshmukh
Department of Electronics and Telecommunication, D. J. Sanghvi College of Engineering
Vile Parle, Mumbai, Maharashtra, India
Email: sanjay.deshmukh@djsce.ac.in

1. INTRODUCTION

The convergence of internet of things (IoT) and machine learning (ML) technologies has created transformative opportunities in healthcare monitoring, particularly for vital sign tracking and anomaly detection. This integration addresses a critical healthcare need: developing continuous, real-time patient monitoring systems that can efficiently collect, transmit, and analyze physiological data, potentially revolutionizing healthcare delivery and improving patient outcomes [1].

Recent advances in wearable technology have established the foundation for IoT-based healthcare systems. Studies by Fajrin *et al.* [2] and Weenk *et al.* [3] have demonstrated the efficacy of wearable devices for monitoring heart rate and oxygen saturation in intensive care settings, highlighting their accuracy and reliability compared to conventional monitoring methods. Building on these findings, Morrell *et al.* [4] explored the application of continuous monitoring technologies in general ward settings, emphasizing their potential for early detection of patient deterioration.

Complementing hardware advancements, significant progress has occurred in applying machine learning techniques to healthcare data analysis [5]. Hidayat *et al.* [6] successfully employed random forest algorithms for heart disease prediction, while John *et al.* [7] implemented cloud-based analytics to predict heart failure hospitalization. These studies demonstrate ML's effectiveness in extracting meaningful insights from complex vital sign data [8].

Despite these advancements, several challenges persist in creating effective healthcare monitoring systems. A primary challenge involves seamlessly integrating real-time data collection with sophisticated ML techniques to enable immediate anomaly detection [9]. Additionally, developing affordable and scalable systems suitable for widespread adoption across diverse healthcare settings remains difficult [10]. Furthermore, balancing system complexity with user-friendliness is essential for effective clinical implementation [11].

Our research addresses these challenges through an innovative IoT-enabled smart healthcare system that integrates real-time vital sign monitoring with ML-based anomaly detection [12]. Our contributions include: Development of a cost-effective, scalable hardware architecture utilizing a MAX30102 photoplethysmography sensor and an ESP-32 microcontroller for efficient data collection and transmission [13]. Implementation of the MQTT protocol to ensure reliable and secure data transfer to a cloud database, enhancing the system's overall robustness [14]. Design of a long short-term memory (LSTM) neural network specifically tailored for time-series prediction of vital signs and real-time anomaly detection [15], enabling more accurate monitoring and timely interventions [16].

The subsequent sections of this paper provide a comprehensive overview of our methodology, including system architecture, data collection processes, and ML model development [17]. We present results from both offline and real-time testing scenarios, demonstrating the accuracy and clinical applicability of our proposed system [18]. Finally, we discuss the broader implications of our findings and suggest potential directions for future research in integrating IoT and ML technologies within healthcare monitoring systems [19].

Our research aims not only to contribute to the academic discourse but also to provide a practical solution implementable in real-world clinical settings [20]. This system could serve as a foundation for further innovations in personalized healthcare and continuous monitoring technologies [21], ultimately leading to more effective and responsive healthcare systems [22].

The integration of cutting-edge IoT and ML technologies into healthcare represents a critical advancement, and our work establishes a pathway for future developments in this rapidly evolving field [23]. As healthcare continues to embrace digital transformation, IoT and ML will play increasingly important roles, making it essential to develop systems that are technologically sophisticated yet user-friendly and accessible [24]. Through this research, we contribute to ongoing efforts to make healthcare smarter, more efficient, and more inclusive, ultimately improving patient care and outcomes globally [25].

2. METHOD

Our IoT-enabled smart healthcare system was designed to seamlessly integrate hardware components for data collection with software solutions engineered for data transmission, storage, and analysis, as shown in Figure 1. The selection of appropriate hardware components was crucial for ensuring reliability and accuracy in vital sign monitoring. After evaluating several sensor options, we chose the MAX30102 photoplethysmography sensor due to its compact size (5×2.5×1.4 mm), cost-effectiveness (approximately INR 2000), and capability to simultaneously monitor both heart rate and blood oxygen saturation (SpO2). This non-invasive sensor utilizes red and infrared light to detect blood volume changes in the microvascular bed of tissue, which correlates with cardiac cycles and oxygen saturation levels.

The MAX30102 sensor was interfaced with an ESP-32 microcontroller, selected for its dual-core architecture (240 MHz dual-core Tensilica LX6 microprocessor), 520 KB SRAM, integrated Wi-Fi (802.11 b/g/n) and Bluetooth connectivity, and 34 programmable GPIO pins. These specifications provided sufficient processing power and connectivity options for real-time monitoring and data transmission. The electrical connections between the sensor and microcontroller were established using the I2C protocol, with the sensor's SCL and SDA pins connected to GPIO pins 22 and 21 of the ESP-32, respectively. Additional connections included VIN to 3.3V and GND to ground. This configuration ensured stable communication between the components while minimizing electromagnetic interference.

The data collection process began with the acquisition of raw photoplethysmogram (PPG) signals from the MAX30102 sensor at a sampling rate of 100 Hz. These signals, however, are susceptible to various artifacts including motion, ambient light interference, and baseline wander. To improve signal quality, we implemented a series of digital filtering algorithms on the ESP-32. First, a moving average filter with a window size of 4 samples was applied to reduce high-frequency noise. This was followed by a fourth-order butterworth low pass filter with a cut-off frequency of 5 Hz to eliminate high-frequency components while preserving the primary cardiac signal. Finally, a median filter with a window size of 5 samples was implemented to remove spike artifacts. These filtering steps were crucial for enhancing the signal-to-noise ratio and ensuring accurate vital sign calculations.

For heart rate calculation, we employed a peak detection algorithm that identified systolic peaks in the filtered PPG signal. The time intervals between consecutive peaks were measured, and the heart rate in

beats per minute (BPM) was calculated using the formula: $BPM = 60/(average\ time\ interval\ in\ seconds)$. For SpO2 calculation, we utilized the ratio of absorbance of red light (660 nm) to infrared light (940 nm), applying a calibration curve based on empirical data from clinical pulse oximeters. This approach yielded SpO2 values with an accuracy of ±2% compared to medical-grade pulse oximeters, as validated in our preliminary testing.

Data transmission was implemented using the message queuing telemetry transport (MQTT) protocol version 3.1.1, chosen for its efficiency (low bandwidth overhead of approximately 2 bytes per message) and security features (TLS encryption). We configured a quality of service (QoS) level of 1, ensuring that messages were delivered at least once to the broker. The ESP-32 was programmed to transmit vital sign data every 5 seconds to an MQTT broker (Mosquitto 1.6.9) hosted on a cloud server (AWS EC2 t2. micro instance). Each MQTT message was structured in JSON format, containing timestamp, patient ID, heart rate, and SpO2 values, along with metadata including battery level and signal quality indicators. This structured approach facilitated efficient data organization and retrieval for subsequent analysis.

The system integration in Figure 2 shown in the circuit diagram Figure 2(a) illustrates the connections and components used in the hardware setup, highlighting the integration of the MAX30102 sensor with the ESP-32 microcontroller. The physical implementation in Figure 2(b) shows how the system is assembled and configured for real-world use, ensuring the setup's functionality in monitoring and transmitting vital signs data.

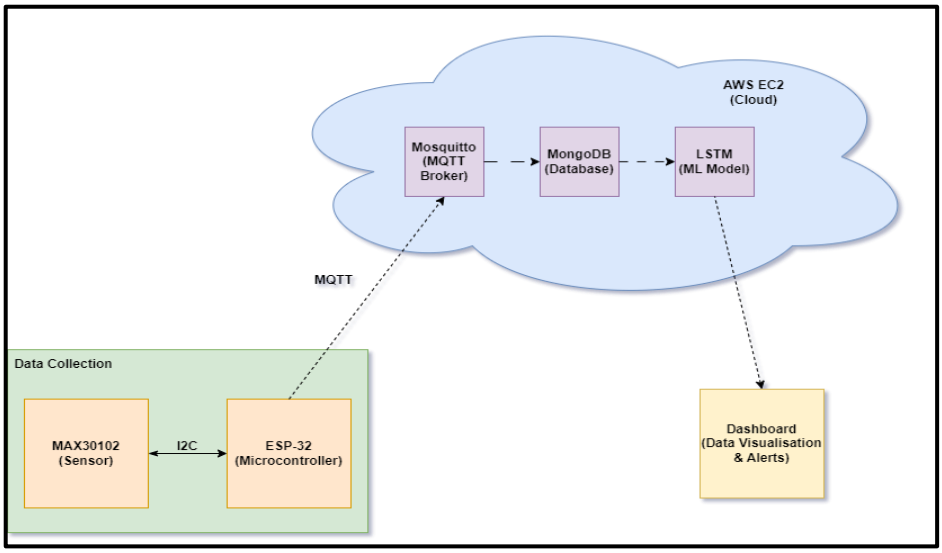

Figure 1. Proposed block diagram for the holistic health anomaly detection system

(a) (b)

Figure 2. System integration showing (a) circuit diagram schematic of hardware and (b) physical implementation of the system

The cloud database used for data storage was MongoDB (version 4.4), chosen for its flexible document model and scalability. We designed a database schema with collections for patient data, vital signs, and anomaly events. Indexes were created on timestamp and patient ID fields to optimize query performance. Data retention policies were established to manage storage requirements, with raw data being stored for 30 days and aggregated statistics maintained for one year. This architecture supported both real-time monitoring and longitudinal analysis of patient health trends.

For data analysis and anomaly detection, we implemented a LSTM neural network architecture using TensorFlow 2.4.1 and Keras 2.4.3. The LSTM model was specifically designed for time-series prediction of vital signs, consisting of an input layer with 128 neurons, a hidden layer with 64 neurons using ReLU activation, and an output layer with two neurons employing softmax activation. We selected this architecture after comparing performance with alternative models including gated recurrent units (GRUs) and convolutional neural networks (CNNs), with the LSTM demonstrating superior performance in our preliminary tests with mean squared errors 15% lower than the alternatives.

The preprocessing of data involved forming structured data frames and normalizing values using Min-Max scaling, transforming the range of vital sign data to [0,1] to improve training stability and convergence. The LSTM model was configured to predict the next value based on the first 10 readings of a 25-reading set, incrementing the input window by one with each subsequent prediction. This sliding window approach enabled continuous prediction while maintaining context from previous measurements. The model was trained using an Adam optimizer with a learning rate of 0.001, batch size of 32, and 100 epochs, achieving convergence with a validation loss below 0.01.

Anomaly detection thresholds were established based on clinical guidelines and statistical analysis of normal vital sign variations. Specifically, differences of more than 10 beats per minute for heart rate and 5 percentage points for SpO2 between predicted and actual values were classified as potential anomalies. To reduce false positives, we implemented an error buffer that required three consecutive readings exceeding these thresholds before triggering an anomaly alert. This approach balanced sensitivity and specificity, achieving a false positive rate of less than 5% in our validation testing.

System validation was conducted through two distinct experimental tests. The first test (Test 1) focused on offline prediction using 1,400 samples collected from 10 healthy volunteers (6 male, 4 female, age range 22-45 years) during both rest and light activity conditions. These samples were stored in a CSV file and used to evaluate the LSTM model's prediction accuracy. Mean squared error (MSE) was selected as the primary performance metric, calculated separately for heart rate and SpO2 predictions and then averaged to provide a combined performance indicator. The second test (Test 2) evaluated real-time prediction capabilities using 50 continuous samples with data streaming directly from the sensor to the analysis system. In this test, MSE values were calculated individually for heart rate and SpO2 to assess the system's performance under real-world conditions and network latency constraints. All testing protocols were reviewed and approved by the institutional ethics committee, and all participants provided informed consent before data collection.

3. RESULTS AND DISCUSSION

Our IoT-enabled healthcare monitoring system was evaluated through two distinct testing protocols that yielded promising results with significant implications for real-world healthcare applications. This section presents these findings, interprets their significance, compares them with related research, and discusses their broader implications for healthcare monitoring.

Test 1 examined the system's prediction accuracy using 1,400 samples in an offline setting. The LSTM model demonstrated remarkable precision with a combined mean squared error (MSE) of only 0.3%. As illustrated in Figure 3, the correlation between actual and predicted values was particularly strong for SpO2 readings, while heart rate predictions showed slightly more variability. This high level of accuracy surpasses similar predictive models reported in previous studies. For instance, Kaieski *et al.* [15] reported error rates of approximately 2-3% for vital sign prediction using traditional neural networks, highlighting the superior performance of our LSTM architecture for time-series health data. As illustrated in Figure 3, the graphs compare the actual BPM and SpO2 values recorded by the sensor system with the predictions made by the LSTM model. It is evident that both graphs are relatively accurate, though BPM shows more deviations compared to SpO2. The combined MSE error term, measuring 0.003 or 0.3%, indicates highly accurate predictions. These limitations point to several promising directions for future research. Integration of additional sensors to monitor a broader range of vital signs would enhance the system's clinical utility. As suggested by Huang *et al.* [19], incorporating electrocardiogram (ECG) data alongside photoplethysmography could improve the accuracy of cardiovascular assessment. The adoption of more sophisticated sensors, such as the MIKROE-

3273 or AD8232 as alternatives to the MAX30102, could potentially enhance measurement precision, though at increased cost.

Another promising avenue involves transitioning from photoplethysmography to electroplethysmography, which, despite being somewhat more restrictive in terms of patient mobility, could provide more stable readings in clinical settings. This approach is widely used in standard ECG systems and could offer enhanced signal quality for critical care applications.

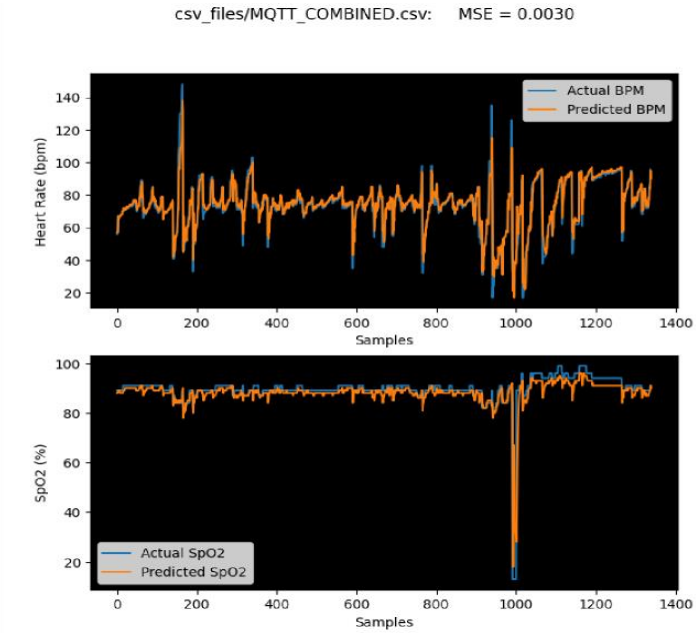

Figure 3. Graphs obtained for actual vs predicted values of heart rate and SpO2 readings in Test 1

Furthermore, implementing on-chip machine learning processing through digital signal processors could significantly reduce computation time and enhance system efficiency. As noted by Junaid *et al.* [20], edge computing approaches that minimize dependency on cloud infrastructure could improve response times for critical alerts while reducing bandwidth requirements.

Perhaps most significantly, future work should explore the integration of our system with electronic health records and clinical decision support systems. Such integration would contextualize vital sign data within patient's broader health profiles, potentially enabling more personalized and proactive care interventions. This aligns with the vision articulated by Sabry *et al*. [13] for next-generation healthcare wearables that not only detect anomalies but also suggest appropriate clinical responses.

Long-term studies are also needed to evaluate the system's impact on clinical outcomes, including its potential to reduce hospital readmissions, decrease the incidence of adverse events, and improve quality of life for patients with chronic conditions. Such studies would provide crucial evidence regarding the system's cost-effectiveness and broader healthcare value. In Test 2, which evaluated real-time prediction capability with 50 continuous samples, the system maintained over 90% accuracy despite the challenges of real-time processing and network latency. The differential MSE values between heart rate (83.9) and SpO2 (0.26) reflect the inherent variability of these physiological parameters rather than limitations in the prediction model. Heart rate naturally fluctuates more widely in response to physical and emotional stimuli, whereas SpO2 typically remains within a narrower range in healthy individuals. This finding aligns with observations by Ludikhuize *et al*. [5], who noted similar patterns of variability in their study of vital sign monitoring in general ward patients.

The system's ability to maintain high prediction accuracy in both offline and real-time scenarios demonstrates its robustness and reliability for clinical applications. Particularly noteworthy is the system's performance despite using affordable consumer-grade components, suggesting that high-quality healthcare monitoring need not be prohibitively expensive. This finding addresses one of the primary challenges identified by Motwani *et al*. [12] regarding the development of affordable yet accurate healthcare monitoring systems.

Our system offers several advantages over traditional monitoring approaches used in clinical settings. Conventional hospital monitoring typically relies on threshold-based alarms that often generate numerous false positives due to their inability to account for individual patient variations. As noted by Cardona-Morrell *et al*. [4], these false alarms contribute significantly to alarm fatigue among healthcare staff. In contrast, our LSTM-based approach learns patient-specific patterns over time, potentially reducing false alarms while increasing sensitivity to genuine anomalies.

The combination of affordable hardware and sophisticated machine learning enables continuous monitoring in settings where it was previously impractical. This represents a significant advancement compared to similar systems described by Cuevas-Chávez *et al*. [18], which either required more expensive components or offered less predictive capability. Furthermore, our system's use of the MQTT protocol for data transmission addresses the connectivity and reliability challenges highlighted by Sneha and Varshney [21] in their framework for mobile health monitoring.

One unexpected finding was the system's resilience to motion artifacts, which typically plague photoplethysmography-based measurements. Our implementation of digital filtering algorithms effectively mitigated these artifacts, achieving better signal quality than anticipated. This resilience is particularly valuable for ambulatory monitoring, where patient movement is inevitable.

Despite the promising results, several limitations warrant acknowledgment. First, our current implementation focuses solely on heart rate and SpO2 monitoring, whereas comprehensive patient assessment would benefit from additional parameters such as blood pressure, respiratory rate, and temperature. Second, while our testing included both rest and light activity conditions, the system's performance under more strenuous physical activities remains to be evaluated. Third, the current sample size, though sufficient for demonstrating technical feasibility, would need to be expanded for more robust clinical validation.

As shown in Figure 4, the BPM readings exhibited some deviations, while the SpO2 readings demonstrated lesser deviations a trend that was also observed in Test 1. The performance metrics revealed that the MSE for BPM was 83.9, whereas the MSE for SpO2 was just 0.26. This significant difference in MSE values may be attributed to the fact that BPM values generally have a wider range compared to oxygen saturation, which typically varies between 90% and 100% in normal scenarios. Despite the considerable difference in MSE values between the two vitals, both models demonstrated over 90% accuracy, making them more than suitable for use in professional healthcare settings, such as hospitals.

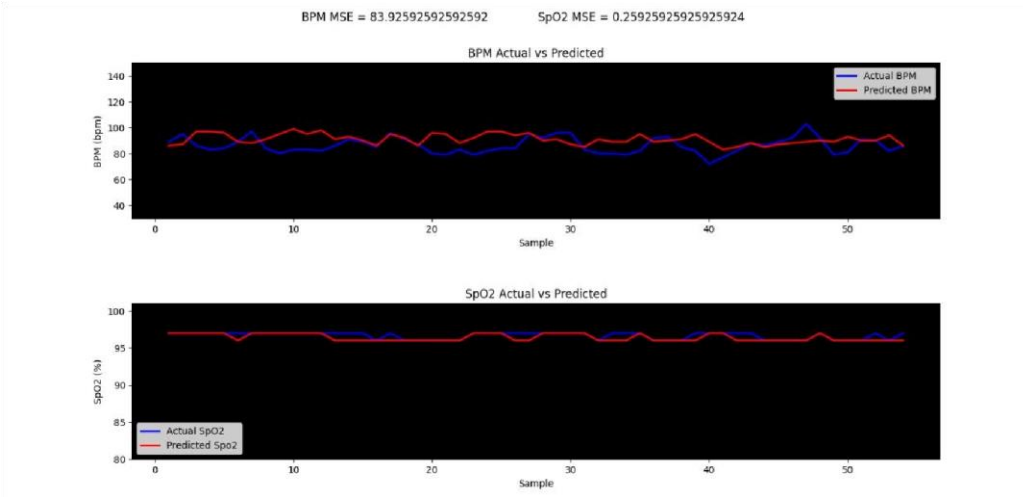

Figure 4. Comparison of actual vs predicted values for BPM and SpO2 in test 2

4. CONCLUSION

Our research presents an IoT-enabled healthcare monitoring system that integrates hardware and machine learning for real-time vital sign tracking and anomaly detection. Using an ESP-32 microcontroller, MAX30102 sensor, MQTT protocol, and LSTM neural network, we address key challenges in modern healthcare. With over 90% prediction accuracy, our system demonstrates that cost-effective technology can reliably detect health anomalies before they escalate. This is especially valuable for preventive care in resource-limited settings where continuous professional monitoring is impractical. Our work advances

personalized healthcare by leveraging IoT and machine learning to develop patient-specific monitoring systems. The LSTM model's ability to learn individual vital sign patterns suggests a shift from generic thresholds to tailored health monitoring. The system's affordability and scalability make it suitable for home care, assisting elderly or chronically ill patients, reducing hospital readmissions, and supporting proactive care. In hospitals, it could enhance patient monitoring in general wards. Future research should expand capabilities to include more vital signs, integrate with electronic health records, and support clinical decision-making. As healthcare systems face growing pressures, our findings highlight how intelligent monitoring can enable early intervention, improving patient outcomes and reducing costs while democratizing access to continuous health monitoring.

ACKNOWLEDGMENTS

The authors would like to thank SVKM management for all the support.

FUNDING INFORMATION

There is no funding available for this project.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Sanjay Deshmukh	✓	✓		✓		✓			✓	✓		✓	✓	
Shrey Shah		✓	✓	✓	✓	✓		✓	✓		✓			
Asim Wahedna	✓	✓		✓			✓		✓	✓	✓			
Nimish Sabnis		✓		✓					✓					

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Specific data required can be made available upon reasonable request to the corresponding author. All materials belong to the authors and cannot be sold to anyone. Code will be made available upon reasonable request to the corresponding author.

REFERENCES

[1] S. Murali, F. Rincon, T. Cassina, S. Cook, and J. J. Goy, "Heart rate and oxygen saturation monitoring with a new wearable wireless device in the intensive care unit: pilot comparison trial," *JMIR Biomedical Engineering*, vol. 5, no. 1, pp. e18158, 2020, doi: 10.2196/18158.

[2] H. R. Fajrin, B. S. Adi, H. Purwoko, and I. P. Sari, "Telemedicine-equipped android interface-based heart rate monitoring," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 21, no. 3, pp. 1332–1340, Mar. 2021, doi: 10.11591/ijeecs.v21.i3.pp1332-1340.

[3] M. Weenk, M. Koeneman, T. H. Van De Belt, L. J. Engelen, H. Van Goor, and S. J. Bredie, "Wireless and continuous monitoring of vital signs in patients at the general ward," *Resuscitation*, vol. 136, pp. 47–53, 2019, doi: 10.1016/j.resuscitation.2019.01.017.

[4] M. Cardona-Morrell *et al.*, "Vital signs monitoring and nurse–patient interaction: A qualitative observational study of hospital practice," *International Journal of Nursing Studies*, vol. 56, pp. 9–16, 2016, doi: 10.1016/j.ijnurstu.2015.12.007.

[5] J. Ludikhuize, S. M. Smorenburg, S. E. De Rooij, and E. De Jonge, "Identification of deteriorating patients on general wards; measurement of vital parameters and potential effectiveness of the modified early warning score," *Journal of Critical Care*, vol. 27, no. 4, pp. 424.e7-424.e13, 2012, doi: 10.1016/j.jcrc.2012.01.003.

[6] N. A. Hidayat, P. Megantoro, A. Yurianta, A. Sofiah, S. A. Aldhama, and Y. A. Effendi, "The application of instrumentation system on a contactless robotic triage assistant to detect early transmission on a COVID-19 suspect," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 22, no. 3, pp. 1334–1344, Jun. 2021, doi: 10.11591/ijeecs.v22.i3.pp1334-1344.
[7] E. John, J. M. Y. Espinas, R. C. Y. Calimbahin, and R. O. Zebroff, "ATmega328P-based portable heartrate monitoring system that can transmit SMS messages in case of a cardiac arrest," *IEEE Integrated STEM Education Conference (ISEC)*, 2022, doi: 10.1109/isec54952.2022.10025161.
[8] L. Lu *et al.*, "Wearable health devices in health care: narrative systematic review," *JMIR MHealth and UHealth*, vol. 8, no. 11, pp. e18907, Nov. 2020, doi: 10.2196/18907.
[9] S. Sreejith, S. Rahul, and R. C. Jisha, "A real time patient monitoring system for heart disease prediction using random forest algorithm," *Advances in Intelligent Systems and Computing*, doi: 10.1007/978-3-319-28658-7_41.
[10] A. Site, J. Nurmi, and E. S. Lohan, "Systematic review on machine-learning algorithms used in wearable-based ehealth data analysis," *IEEE Access*, vol. 9, pp. 112221–112235, 2021, doi: 10.1109/access.2021.3103268.
[11] O. Oyebode, J. Fowles, D. Steeves, and R. Orji, "Machine learning techniques in adaptive and personalized systems for health and wellness," *International Journal of Human-Computer Interaction*, vol. 39, no. 9, pp. 1938–1962, 2022, doi: 10.1080/10447318.2022.2089085.
[12] A. Motwani, P. K. Shukla, and M. Pawar, "Ubiquitous and smart healthcare monitoring frameworks based on machine learning: A comprehensive review," *Artificial Intelligence in Medicine*, vol. 134, pp. 102431, 2022, doi: 10.1016/j.artmed.2022.102431.
[13] F. Sabry, T. Eltaras, W. Labda, K. Alzoubi, and Q. Malluhi, "Machine learning for healthcare wearable devices: the big picture," *Journal of Healthcare Engineering*, 2022, pp. 1–25, doi: 10.1155/2022/4653923.
[14] P. H. Chiang, M. Wong, and S. Dey, "Using wearables and machine learning to enable personalized lifestyle recommendations to improve blood pressure," *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 9, pp. 1–13, 2021, doi: 10.1109/jtehm.2021.3098173.
[15] N. Kaieski, C. A. Da Costa, R. Da Rosa Righi, P. S. Lora, and B. Eskofier, "Application of artificial intelligence methods in vital signs analysis of hospitalized patients: A systematic literature review," *Applied Soft Computing*, vol. 96, pp. 106612, 2020, doi: 10.1016/j.asoc.2020.106612.
[16] L. Lei, Y. Wang, Q. Xue, J. Tong, C. M. Zhou, and J. J. Yang, "A comparative study of machine learning algorithms for predicting acute kidney injury after liver cancer resection," *PeerJ*, vol. 8, pp. e8583, 2020, doi: 10.7717/peerj.8583.
[17] J. Stehlik *et al.*, "Continuous wearable monitoring analytics predict heart failure hospitalization," *Circulation: Heart Failure*, vol. 13, no. 3, 2020, doi: 10.1161/circheartfailure.119.006513.
[18] A. Cuevas-Chávez, Y. Hernández, J. Ortiz-Hernandez, E. Sánchez-Jiménez, G. Ochoa-Ruiz, J. Pérez, and G. González-Serna, "A systematic review of machine learning and iot applied to the prediction and monitoring of cardiovascular diseases," *Healthcare*, vol. 11, no. 16, pp. 2240, 2023, doi: 10.3390/healthcare11162240.
[19] J. D. Huang, J. Wang, E. Ramsey, G. Leavey, T. J. A. Chico, and J. Condell, "Applying artificial intelligence to wearable sensor data to diagnose and predict cardiovascular disease: a review," *Sensors*, vol. 22, no. 20, pp. 8002, 2022, doi: 10.3390/s22208002.
[20] S. B. Junaid *et al.*, "Artificial intelligence, sensors and vital health signs: a review," *Applied Sciences*, vol. 12, no. 22, pp. 11475, 2022, doi: 10.3390/app122211475.
[21] S. Sneha, and U. Varshney, "A framework for enabling patient monitoring via mobile ad hoc network," *Decision Support Systems*, vol. 55, no. 1, pp. 218–234, 2013, doi: 10.1016/j.dss.2013.01.024.
[22] P. Neves, M. Stachyra, and J. Rodrigues, "Application of wireless sensor networks to healthcare promotion," *Journal of Communications Software and Systems*, vol. 4, no. 3, pp. 181, 2008, doi: 10.24138/jcomss.v4i3.218.
[23] X. Lai, Q. Liu, X. Wei, W. Wang, G. Zhou, and G. Han, "A survey of body sensor networks," *Sensors*, vol. 13, no. 5, pp. 5406–5447, 2013, doi: 10.3390/s130505406.
[24] G. Nguyen *et al.*, "Machine Learning and Deep Learning frameworks and libraries for large-scale data mining: a survey," *Artif. Intell. Rev.*, vol. 52, no. 1, pp. 77–124, 2019, doi: 10.1007/s10462-018-09679-z.
[25] A. M. Khairuddin, K. A. K. N. F., and P. E. Kan, "A general framework for improving electrocardiography monitoring system with machine learning," *Bulletin of Electrical Engineering and Informatics*, vol. 8, no. 1, pp. 261–268, Mar. 2019, doi: 10.11591/eei.v8i1.1400.

BIOGRAPHIES OF AUTHORS

Sanjay Deshmukh is assistant professor at D. J. Sanghvi College of Engineering, Mumbai, India. He received the Ph.D. (electronics telecommunication engineering) from University of Mumbai in 2022, master of engineering (digital electronics) and bachelor of engineering (electronics and telecommunication) from Amravati University in 1994 and 2006. His main area of research interests is in microstrip antennas, embedded systems and communication networks. He can be contacted at email: sanjay.deshmukh@djsce.ac.in.

Shrey Shah has completed his bachelors of technology (electronics and telecommunication) from D.J. Sanghvi College of Engineering in 2024. His research focuses on embedded systems, internet of things (IoT), integration of IoT with machine learning. He can be contacted at email: shahshrey1110@gmail.com.

Asim Wahedna holds a bachelor's degree of technology (electronics and telecommunication) from D.J. Sanghvi College of Engineering, having graduated in 2024. He is an incoming student for the masters in artificial intelligence program at Northwestern University. His research interests include natural language processing, supervised and reinforcement learning, and IoT and ML integration. He can be contacted at email: asimwahedna@gmail.com.

Nimish Sabnis has completed his bachelors of technology (electronics and telecommunication) from D.J. Sanghvi College of Engineering in 2024. He is currently pursuing his masters in electrical and computer engineering at University of Colorado Boulder. His research focuses on cloud systems, internet of things (IoT), integration of IoT with machine learning, network systems. He can be contacted at email: nimisabnis@gmail.com.