A Cloud-Enabled Autonomous Telemedicine Platform for Continuous ECG Monitoring and Arrhythmia Classification

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Abstract

The Medical Internet of Things (MIoT), also known as telemedicine, has emerged as a promising paradigm for the continuous monitoring of patients' vital signs, while Artificial Intelligence (AI) has shown strong potential in healthcare applications, particularly for automated biosignal analysis. However, existing research has typically focused either on biosignal acquisition systems or on the development of deep learning models in isolation, with limited implementation in an integrated framework. This paper presents an autonomous IoT-based healthcare system for electrocardiogram (ECG) monitoring, integrated with an attention-based deep learning model for ECG signal classification. The developed cloud-integrated IoT platform enables the acquisition and storage of ECG signals while leveraging server-side computational resources for automated analysis and prediction. The proposed telemedicine system consists of a wearable device for ECG acquisition and a central server implementing deep learning models for five-class arrhythmia classification. The model achieved an accuracy of 99.0%, a precision of 93.6%, a recall of 90.8%, and an F1-score of 92.0%. To promote reproducibility and further research, the implementation of the proposed system is publicly available on GitHub (https://github.com/AlexTran1703/telemedicine-system). These findings demonstrate the feasibility of integrating IoT infrastructure with deep learning for remote ECG monitoring and automated arrhythmia classification, and support the potential of AI-enabled MIoT systems for scalable and efficient cardiovascular monitoring.

Keywords: Medical Internet of Things, telemedicine, electrocardiogram, arrhythmia, artificial intelligence, deep learning

1 Introduction

Cardiovascular diseases (CVDs) are among the leading causes of mortality worldwide. In 2019, they accounted for approximately 32% of all global deaths [1]. This high prevalence is partly associated with inadequate long-term monitoring and inconsistent treatment. In response, telemedicine—a branch of MIoT that enables interactions between patients and healthcare providers through connected electronic devices—has emerged as a modern solution within healthcare systems. Today, vital physiological parameters such as blood oxygen saturation (SpO_2), heart rate, and electrocardiogram (ECG) signals can be remotely and continuously monitored using modern wearable and IoT-enabled technologies. These non-invasive biosignal measurements provide valuable insights into a patient's health status while ensuring convenience, particularly for individuals living far from healthcare centers [2].

Recent studies have demonstrated the growing effectiveness of remote vital-sign monitoring systems in telemedicine applications. Jae-Ho Lee et al. developed an implantable ECG monitoring system that integrates wireless charging and real-time data transmission. The system was validated through animal skin tests, and the data collected from the implanted device could be accessed via a clinical terminal. Communication between the device and the monitoring platform was established through Bluetooth [3]. James Heaney et al. presented a comprehensive ECG monitoring system capable of capturing and displaying a patient's heart signals, heart rate, blood oxygen saturation, and body temperature. The collected data can be visualized on an OLED display, a smartphone via Bluetooth, or a computer via serial communication for further analysis using MATLAB [4]. Furthermore, Chuchart Pintavirooj et al. proposed a multi-parameter telemedicine system utilizing WebSocket technology to remotely monitor six vital-sign parameters, including electrocardiogram, temperature, plethysmogram, oxygen saturation, blood pressure, and heart rate. The system operates over a 4G mobile network and achieves a communication latency of less than 5 ms [5]. In another study, Sarjerao and Prakasarao proposed a system for monitoring vital parameters such as body temperature, SpO_2, pulse rate, and movement across a large number of clients. The system visualizes patient data on an MQTT server and provides continuous health-condition analysis along with treatment recommendations [6]. Ionel Zagan et al. proposed a portable single-lead ECG recorder that supports multiple operational modes, including Bluetooth and Global System for Mobile Communications (GSM) transmission, enabling real-time monitoring and supporting both local and remote health assessment [7]. Finally, Jaime A. Rincon et al. proposed a fog-computing-based platform structured into three layers. Layer I is responsible for capturing and transmitting physiological parameters such as PPG, ECG, SpO_2, and PCG to Layer II via the LoRa communication protocol. Layer II, powered by AI, analyzes ECG signals using deep learning techniques to support early cardiac abnormality assessment. The results are subsequently transmitted to Layer III, which functions as the cloud layer for secure data storage, management, and advanced analytics [8].

Beyond biometric monitoring systems, a substantial body of research in healthcare has focused on the application of Artificial Intelligence (AI) for disease diagnosis and prediction [9]. This includes the use of deep learning algorithms to classify specific medical conditions, such as lung cancer using chest X-ray images [10] and brain tumors using MRI images [11]. Other studies have explored AI applications using physiological signals, such as SpO_2 for sleep apnea detection [12] and ECG for arrhythmia detection [13, 14]. In addition, several studies have proposed deep learning model architectures trained on the MIT-BIH dataset [15], including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, achieving accuracies of 95.2% [16], 98.63% [17], and 98% [18].

While existing studies primarily focus either on telehealth-based vital-sign monitoring frameworks or on deep learning models for disease classification, these approaches often address only isolated components of a broader smart healthcare ecosystem. In addition, many proposed solutions require substantial computational resources, which limits their applicability in lightweight or resource-constrained deployments. To address these limitations, this paper presents a deep learning model trained on the MIT-BIH dataset for arrhythmia classification and introduces a comprehensive cloud-based telemedicine platform that incorporates the proposed model for ECG monitoring and automated analysis in home settings. The proposed system consists of a wearable device designed to capture ECG signals and a distributed cloud-based server infrastructure. The server manages communication with ECG devices, performs automated analysis, and stores the results in a database for further review. The system is designed to require minimal user-side configuration, thereby improving scalability, accessibility, and real-time health assessment while reducing technical barriers for end users. The remainder of this paper is organized as follows: Section 2 details the materials and design of the proposed healthcare platform. Section 3 presents the system performance results. Section 4 compares these findings with related studies. Section 5 concludes the paper.

2 Methodology

2.1 System Overview

Figure 1 shows an overview of the proposed system, which consists of smart wearable healthcare devices and a centralized healthcare server. The edge devices are designed to be low-cost, lightweight, and energy-efficient, with limited on-device computational capability. Therefore, computationally intensive tasks are offloaded to the cloud-based server for processing. The cloud service manages IoT devices, deploys the proposed hybrid deep learning model for real-time ECG analysis, and provides web-based services that allow users to access and review their health records remotely.

The deep learning model was trained using the MIT-BIH Arrhythmia Database [13–18], a widely used dataset for ECG arrhythmia classification. The dataset comprises five heartbeat classes: normal beat (N), supraventricular premature beat (S), premature ventricular contraction (P), fusion of ventricular and normal beat (F),

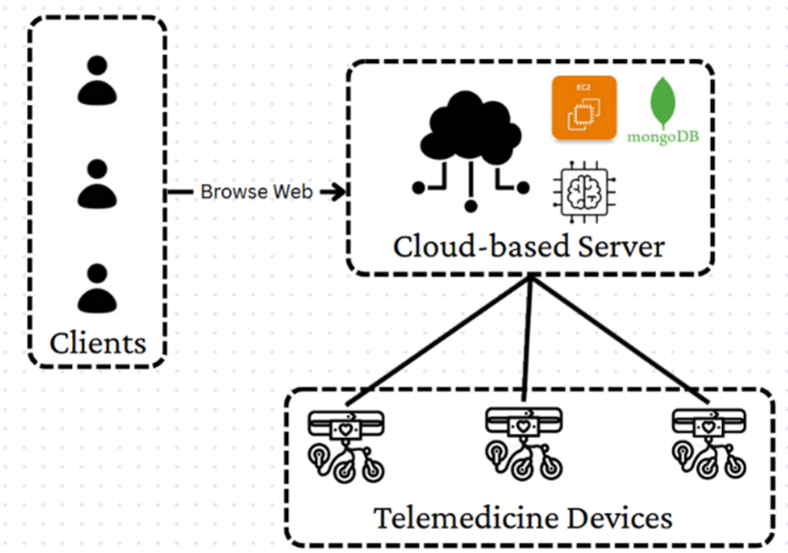


Fig. 1: Overview of the proposed telemedicine system architecture

and unclassifiable beat (U). The trained model was subsequently deployed on the cloud-based server to perform automated ECG-based arrhythmia analysis.

2.2 Cloud-based Telemedicine Platform

The cloud-based telemedicine platform integrates two main components: (i) a wearable device for ECG signal acquisition and server-side synchronization, and (ii) a centralized server responsible for data management and deep learning inference.

The wearable telemedicine device, measuring 4 cm × 4 cm as shown in Figure 2, integrates an ESP8266 microcontroller with wireless communication capabilities, an AD8232 analog front-end for electrocardiogram (ECG) signal acquisition [19], and an SD card module for local storage of ECG data. The device also includes user interface components such as tactile buttons and an OLED display, allowing users to initiate recordings and monitor session status in real time.

ECG signals are acquired and transmitted to the cloud-based server via Wi-Fi using the HTTP protocol. A RESTful communication architecture is adopted to enhance interoperability and scalability across diverse IoT environments. The transmitted payload is formatted in JSON and consists of three primary fields: (1) a static device identifier uniquely assigned to each wearable unit, (2) a configurable patient name field that enables flexible device-to-user assignment, and (3) an ECG signal array representing time-series data sampled at 150 Hz.

Within the cloud-based system, Kubernetes is employed as the orchestration framework to manage resources and control system operations, thereby improving service efficiency and enabling scalability to support a large number of clients [20, 21]. Elastic resource provisioning is achieved through Amazon Web Services (AWS) EC2 instances,

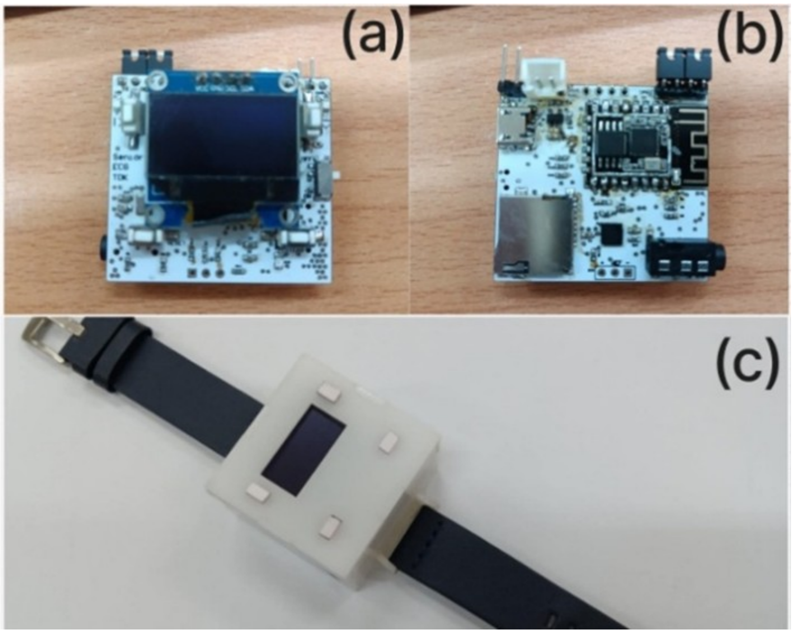


Fig. 2: Wearable device for ECG monitoring

which dynamically scale computational capacity in response to fluctuations in physiological data processing demand. Each EC2 instance hosts the deep learning model for diagnostic inference, while MongoDB serves as the primary database, providing efficient management of unstructured and semi-structured data through its flexible document-oriented schema. This architecture is particularly suitable for healthcare applications that require seamless integration and rapid retrieval of heterogeneous data types, including physiological signals, metadata, and annotations, to support time-sensitive analytics. The system is deployed with up to three EC2 instances, each functioning as an independent full-service server capable of receiving ECG data, performing inference, and storing the results in the cloud-based MongoDB database. As illustrated in Figure 3, the microservice-based design enables service discovery and load balancing by directing incoming RESTful requests to the most appropriate EC2 instance available.

Although deep learning models provide robust feature extraction capabilities, preprocessing remains a critical step to ensure that input data are properly structured while retaining essential diagnostic characteristics. In ECG analysis, the PQRST waveform is fundamental for identifying cardiac abnormalities [16]. To preserve these morphological features, preprocessing involves segmenting ECG recordings into individual heartbeats for model training [13, 16–18]. The process begins with signal normalization to a [0, 1] range to ensure uniform scaling. R-peaks are then detected as reference points for beat segmentation. Each beat is extracted over a duration of 1.2T, where T represents the interval between consecutive R-peaks. Finally, zero-padding

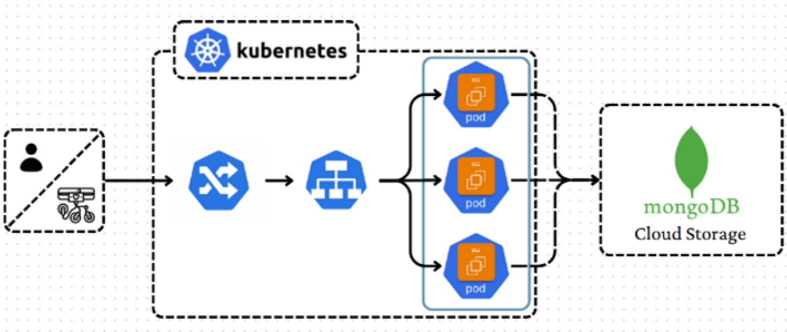


Fig. 3: Microservice architecture of the proposed healthcare service

is applied to standardize the length of each beat signal to 187 samples. This preprocessing pipeline is also implemented on the deployed Amazon EC2 instances, enabling incoming ECG data to be automatically normalized, segmented, and prepared for real-time prediction, as illustrated in Figure 4.

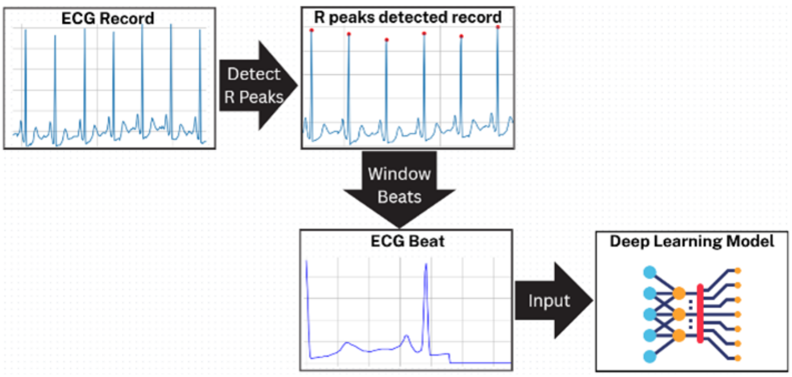


Fig. 4: ECG signal preprocessing pipeline

Beyond device management and automated analysis, each dedicated instance also integrates a web-based interface coupled with a user management system. This framework enables clients to securely access their health records and analysis results. The interface is designed to be intuitive and user-friendly, allowing both patients and healthcare professionals to visualize, track, and manage medical data in real time. Meanwhile, the user management system enforces personalized access control mechanisms to ensure that sensitive information, such as patient health records, is accessible only to authorized individuals. By centralizing data retrieval and supporting real-time updates of patient records, the system improves both the efficiency and accessibility of telemedicine services.

2.3 Deep Learning Model Architecture

In this study, the MIT-BIH Arrhythmia Database is employed for model training. The dataset consists of ECG recordings from 47 subjects, including 23 records randomly selected from a pool of 4,000 24-hour ECG recordings. These recordings were collected at Beth Israel Hospital in Boston, with approximately 60% obtained from inpatients and 40% from outpatients. Each ECG signal was sampled at 360 Hz per channel with 11-bit resolution over a 10 mV range, and all heartbeats were clinically annotated. After preprocessing and segmentation, a total of 109,456 heartbeats were extracted and categorized into five classes: Normal (N), Supraventricular premature beat (S), Premature ventricular contraction (P), Fusion of ventricular and normal beat (F), and Unclassifiable beat (U). The class distributions were as follows: N = 90,589, S = 2,779, P = 7,236, F = 803, and U = 8,039. This distribution highlights a pronounced class imbalance, with normal beats representing approximately 82% of the dataset, while classes S and F account for only 2.5% and 0.7%, respectively. Despite this imbalance, the proposed model demonstrates robust classification performance.

The proposed deep learning architecture, illustrated in Figure 5, integrates Convolutional Neural Networks (CNNs), Gated Recurrent Unit (GRU) networks, and a multi-head attention mechanism. The CNN layers perform feature extraction by applying local convolutional kernels to capture relevant morphological patterns in the ECG signal, thereby generating compact feature representations. GRU networks, a simplified variant of Long Short-Term Memory (LSTM) networks, combine the hidden state and memory cell into a unified structure, providing higher computational efficiency while maintaining the ability to model temporal dependencies and mitigate the vanishing gradient problem [22]. The multi-head attention mechanism further enhances the architecture by enabling parallel extraction of features from multiple perspectives, allowing the model to attend to distinct temporal or morphological aspects of the ECG signal that cannot be fully captured by convolutional layers alone [23].

The architecture is designed around a feature extraction block, which consists of two cascaded convolutional layers (window size = 32, filter size = 16). Their output is concatenated with the output of a parallel convolutional layer (window size = 16, filter size = 6). This fusion of deep and shallow features reduces the risk of overfitting and is conceptually aligned with residual network design. The concatenated output then undergoes max pooling to reduce dimensionality and ReLU activation to introduce non-linearity. This feature extraction block is repeated three times to progressively learn hierarchical representations of the ECG signal. The resulting features are then passed through a multi-head attention layer, followed by GRU layers to capture temporal dependencies within the signal sequence. Finally, the learned representation is flattened and fed into two fully connected layers, each consisting of 32 neurons. The classification stage is implemented using a softmax layer that outputs the probability distribution across the five heartbeat classes.

Model development was implemented using TensorFlow and scikit-learn. The training procedure employed categorical cross-entropy as the loss function and the Adam optimizer with a learning rate of 0.01. The model was trained for 50 epochs using a batch size of 32.

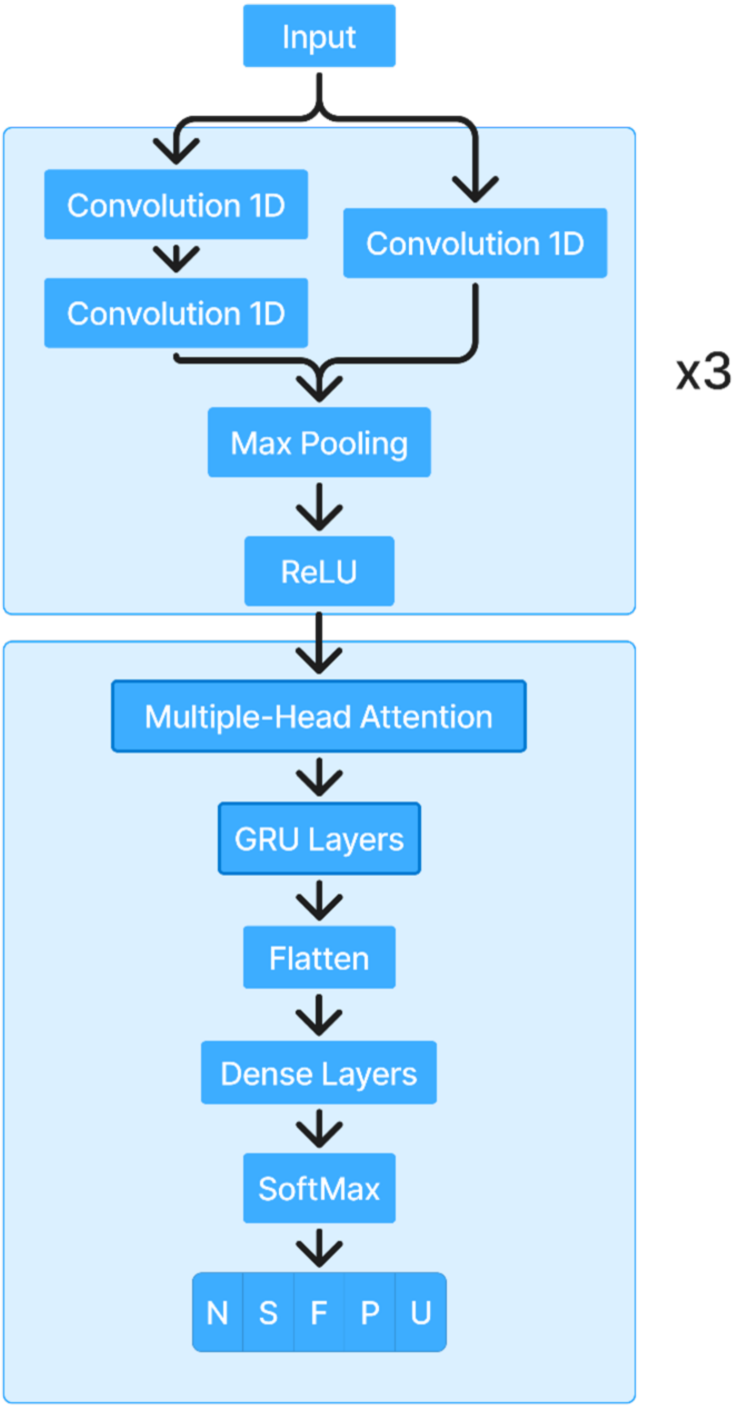


Fig. 5: Proposed deep learning model architecture

3 Experimental Results

3.1 Performance of the Proposed Deep Learning Model

The proposed model is evaluated on the test set using several performance metrics, including accuracy, precision, recall, and F1-score. Accuracy, as defined in equation 1, calculates the proportion of correct predictions among all predictions. Precision, defined in equation 2, is the ratio of true positives (TP) to the sum of true positives (TP) and false positives (FP), indicating how many predicted positive instances are correct. Recall, as defined in equation 3, represents the ratio of true positives (TP) to the sum of true positives (TP) and false negatives (FN), reflecting the model's ability to identify relevant positive instances. The F1-score, described in equation 4, represents the harmonic mean of precision and recall. A higher F1-score indicates a better balance between precision and recall, reflecting the model's overall effectiveness in classification tasks.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

- TP: a positive sample correctly predicted as belonging to the positive class
- FP: a negative sample incorrectly predicted as belonging to the positive class
- TN: a negative sample correctly predicted as belonging to the negative class
- FN: a positive sample incorrectly predicted as belonging to the negative class

The macro and overall accuracies of the model are 93% and 99%, respectively. Table 1 presents the overall performance of the model. The F1-score of all classes exceeded 80%, with classes S and F having the lowest values at 84% and 82%, respectively. Notably, classes S and F constitute only 2.5% and 0.7% of the total dataset, respectively. By incorporating GRUs and multi-head attention mechanisms, the model improves learning for these minority classes, resulting in better performance despite their underrepresentation in the dataset. In contrast, classes N, P, and U achieve F1-scores above 96%, demonstrating the model's strong performance in correctly identifying patterns within these classes. The confusion matrix, shown in Figure 6, indicates that classes N, P, and U have recall values of 99%, 94%, and 99%, respectively, indicating strong classification performance from these classes. Class S achieves a recall of 80.4%, with approximately 18% of its samples misclassified as class N. This misclassification may be attributed to similarities in morphological patterns between classes S and N, particularly variations in PR interval duration. Similarly, class F achieves a recall of 82%, with approximately 12% of its samples misclassified as class N. This may occur because class F contains both normal and ventricular beats, which can overlap with patterns seen in class N.

Table 1: Performance of the proposed model on the test set

Class	Precision (%)	Recall (%)	F1-score (%)	Samples
N	99.0	100.0	99.0	18,118
S	89.0	80.0	84.0	556
P	98.0	94.0	96.0	1,448
F	82.0	83.0	82.0	162
U	100.0	97.0	99.0	1,608
Overall	93.6	90.8	92.0	21,892

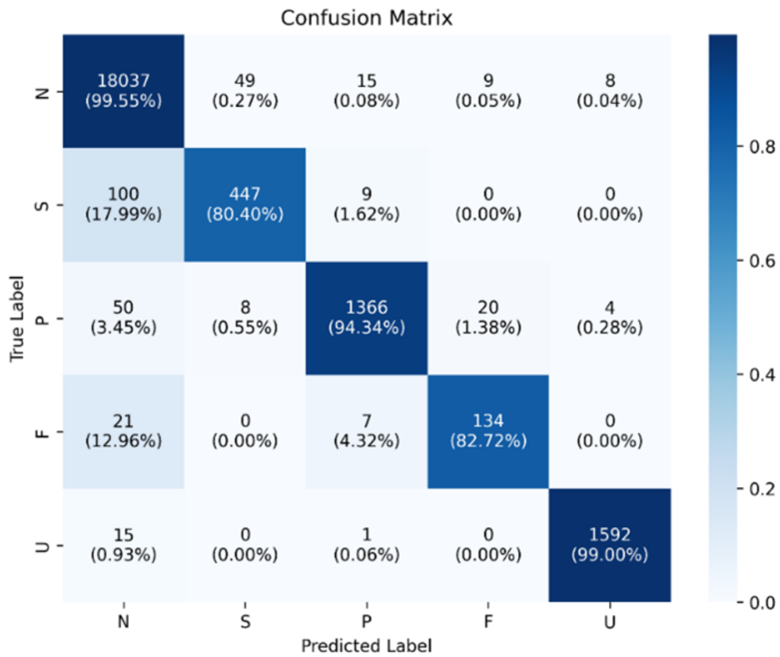
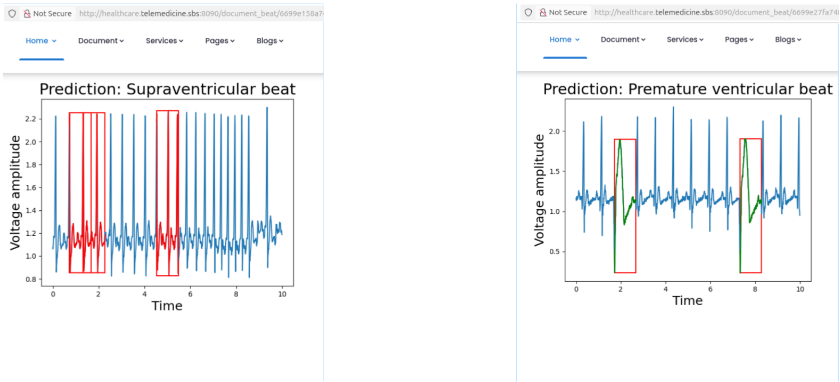


Fig. 6: Confusion matrix of the proposed model

3.2 Experimental Evaluation of the Cloud-Enabled Healthcare System

During the experimental phase, participants were instructed to remain seated and relaxed throughout the recording sessions. ECG signals were acquired in 10-second intervals using a standard Lead II configuration. The study cohort consisted of ten male participants aged 19–39 years. To supplement these measurements, the ADS ECG Simulator SIM II [24] was employed under identical environmental conditions to generate reference waveforms representing a variety of cardiac patterns.



(a) Participant after exercise (b) ECG signal generator

Fig. 7: Detection results under two testing conditions

Each ECG segment was transmitted to an AWS-hosted platform, where automated preprocessing and classification were performed using the deployed deep learning model. The processed physiological data, along with the corresponding outputs, were stored in a cloud-based MongoDB database. Access to these records was secured via a cloud authentication system, enabling authorized users to retrieve their history. In addition, the system offered real-time visualization through a web interface, where users could review prediction results immediately after transmission. Abnormal heartbeats were highlighted with distinct colors. For classification purposes, each ECG segment was labeled as abnormal if at least one abnormal beat type was detected; otherwise, the segment was categorized as normal.

In practical testing, approximately 100 hours of ECG data were collected, consisting of 50 hours from healthy participants and 50 hours generated by the ADS ECG Simulator SIM II [24] to simulate pathological rhythms. Under baseline conditions, with participants in a relaxed state, the system consistently identified normal sinus rhythm (N). In contrast, ECG recordings obtained following physical exertion or under conditions associated with elevated heart rate frequently exhibited supraventricular premature beats (S). Figure 7 shows the detection results under two testing conditions. Figure 7a presents the results obtained from a participant after exercise, where supraventricular premature beats (S) were observed, whereas Figure 7b shows the results obtained using the ECG signal generator, which generated premature ventricular contractions (P) that were accurately detected by the proposed model. The abnormal beats were precisely localized, with red bounding boxes indicating the detected events.

4 Discussion

In contrast to earlier studies that primarily emphasized the transmission and visualization of physiological data [3–7], many existing frameworks depend on an intermediate access layer—typically a base station or computer—for data routing and management

[8]. For instance, James Heaney et al. developed an implantable ECG system transmitting via Bluetooth, but both the device and the vital sign monitor required continuous connection to a base station, thereby necessitating additional hardware [3]. Similarly, Chuchart Pintavirooj et al. proposed a multi-parameter monitoring platform based on WebSocket technology; however, its reliance on a PC connection substantially limited portability [5]. Ionel Zagan et al. designed a portable physiological recorder capable of Bluetooth and GSM transmission; however, its functionality was limited to data transmission without integrated diagnostic capability [7]. By comparison, the system presented in this research constitutes an integrated telemedicine solution encompassing ECG acquisition, wireless transmission, real-time visualization, and automated arrhythmia analysis, all without the need for an intermediate access layer. The design further prioritizes minimal user-side configuration, thereby improving usability and scalability in real-world applications.

With respect to deep learning, the proposed model addresses dataset imbalance without resorting to conventional augmentation or resampling techniques, such as data replication [25]. While such methods can improve recall for minority classes, they often distort the natural data distribution and risk amplifying noise, thereby degrading precision. The present model, based on CNN, GRU, and multi-head attention, is trained directly on the original MIT-BIH dataset and achieves an overall F1-score of 92%. By comparison, Mayank et al.'s CNN approach [16], which incorporated resampling to balance class sizes, achieved an overall F1-score of 87.6%. Although their recall for minority classes S and F reached 84% and 89%, respectively, precision dropped to 71% and 57%, resulting in unstable performance. In contrast, the proposed model achieved F1-scores of 84% for class S and 82% for class F, with balanced recall (80% and 83%) and precision (82% and 83%), demonstrating more consistent classification across both majority and minority classes.

Other studies highlight different trade-offs. Mohammad Rafi [18] integrated LSTM into CNN architectures to enhance long-term feature retention. However, despite achieving higher precision (86% for class F and 80% for class S), recall values were notably lower (63% and 71%), resulting in F1-scores of 73% and 75%. Moreover, LSTM-based architectures demand greater computational resources. In comparison, the GRU-based approach employed in this study offers improved recall and overall performance while maintaining efficiency. Fahad Khan et al. [17] reported CNN–RNN models with performance comparable to this work, but their contributions remained at the algorithmic level without extending into practical telemedicine implementations. By contrast, the current research not only achieves competitive performance but also emphasizes integration into a functional healthcare system for real-time ECG monitoring and arrhythmia analysis, thereby helping bridge the gap between theoretical models and real world deployment.

Beyond diagnostics, the platform facilitates the creation of new cardiovascular datasets by systematically collecting ECG signals from wearable edge devices and storing them in a structured format within a cloud-based database. This dual functionality supports continuous patient care while simultaneously contributing to long-term clinical research. By capturing high-resolution physiological signals under diverse conditions, the system enables large-scale data analysis, iterative model refinement, and the development of more personalized cardiovascular monitoring strategies.

The 100-hour experimental study further provided practical insights into system performance and user interaction. Consistent with clinical expectations, the importance of patient relaxation during ECG acquisition was confirmed. Nevertheless, several limitations were observed. Signal reliability was adversely affected by motion artifacts and powerline interference, both of which degraded ECG quality and impaired classification accuracy [4]. A further challenge was the lack of real patient datasets with clinically confirmed cardiovascular conditions, limiting the model's ability to generalize fully to clinical environments.

Despite these constraints, the study demonstrates the feasibility of combining an affordable wearable device (under $30) with cloud-based computation and storage for scalable telemedicine. However, certain critical aspects remain unaddressed, such as detailed power consumption analysis and the incorporation of advanced digital signal processing techniques for biomedical signals. These limitations underscore persistent challenges in telemedicine research, where studies often prioritize selected system features at the expense of broader practical considerations.

5 Conclusion

In conclusion, this work presents an end-to-end telemedicine solution based on a microservices architecture, designed to support scalable deployment with high availability, reliability, and fault-recovery capability. Within this cloud-native framework, an ECG arrhythmia classification model was implemented and achieved an accuracy of 99%, with a precision of 93.6%, a recall of 90.8%, and an F1-score of 92%. Rather than treating AI model development and telemedicine infrastructure as separate problems, the study integrates both into a unified system that connects advanced deep learning with practical healthcare delivery. The platform also provides a clear path for future extensions, including improved cloud security mechanisms, the integration of smaller and more energy-efficient wearable devices, and the adoption of advanced biomedical signal processing techniques to further improve ECG monitoring and arrhythmia classification in telemedicine settings.

Author Contributions. Khanh Duy Tran was responsible for the overall conception and execution of the project, including the development of the ECG recording hardware, the design and implementation of the artificial intelligence algorithms, system integration, and preparation of the manuscript, including the introduction, methodology, and results sections. Hoa Duc Tong developed and deployed the cloud-based server infrastructure. Minh Nhat Doan and Ly Thi Khanh Vu conducted the experimental setup, system testing, and contributed to the experimental evaluation section. Uyen Dinh Nguyen and Quoc Tan Huynh provided supervision, technical guidance, and critical review of the manuscript. All authors have read and approved the final version of the manuscript.

Data Availability. The ECG dataset used in this study is publicly available. Details of the data source are provided in [26].

Declarations

- **Conflict of interest** The authors declare no competing interests.
- **Ethics approval** The wearable ECG device developed in this study was used to record physiological signals from volunteer participants for system development and evaluation. All procedures were conducted in accordance with relevant institutional guidelines and ethical standards.
- **Consent to Participate** Informed consent was obtained from all participants prior to ECG data collection.
- **Consent for publication** Not applicable.

References

[1] World Health Organization: Cardiovascular Diseases (CVDs). https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds) Accessed 2021-06-11

[2] Yu, Y., Jain, B., Anand, G., Heidarian, M., Lowe, A., Kalra, A.: Technologies for non-invasive physiological sensing: Status, challenges, and future horizons. Biosensors and Bioelectronics: X **16**, 100420 (2024) https://doi.org/10.1016/j.biosx.2023.100420

[3] Lee, J.-H., Seo, D.-W.: Development of ecg monitoring system and implantable device with wireless charging. Micromachines **10**(1), 38 (2019) https://doi.org/10.3390/mi10010038

[4] Heaney, J., Buick, J., Hadi, M.U., Soin, N.: Internet of things-based ecg and vitals healthcare monitoring system. Micromachines **13**(12), 2153 (2022) https://doi.org/10.3390/mi13122153

[5] Pintavirooj, C., Keatsamarn, T., Treebupachatsakul, T.: Multi-parameter vital sign telemedicine system using websocket for covid-19 pandemics. Healthcare **9**(3), 285 (2021) https://doi.org/10.3390/healthcare9030285

[6] Sarierao, B.S., Prakasarao, A.: Smart healthcare monitoring system using mqtt protocol. In: Proceedings of the 3rd International Conference on Convergence in Technology (I2CT), Pune, India, pp. 1–5 (2018). https://doi.org/10.1109/I2CT.2018.8529764

[7] Zagan, I., Găitan, V., Petrariu, A.-I., Iuga, N., Brezulianu, A.: Design, fabrication, and testing of an iot healthcare cardiac monitoring device. Computers **9**(1), 15 (2020) https://doi.org/10.3390/computers9010015

[8] Rincon, J.A., Guerra-Ojeda, S., Carrascosa, C., Julian, V.: An iot and fog computing-based monitoring system for cardiovascular patients with automatic ecg classification using deep neural networks. Sensors **20**(24), 7353 (2020) https://doi.org/10.3390/s20247353

[9] Alowais, S.A., Alghamdi, S.S., Alsuhebany, N., Alqahtani, T., Alshaya, A.I., Almohareb, S.N., Aldairem, A., Alrashed, M., Bin Saleh, K., Badreldin, H.A., Al Yami, M.S., Al Harbi, S., Albekairy, A.M.: Revolutionizing healthcare: The role of artificial intelligence in clinical practice. BMC Medical Education **23**(1), 689 (2023) https://doi.org/10.1186/s12909-023-04698-z

[10] Shimazaki, A., Ueda, D., Choppin, A., Yamamoto, A., Honjo, T., Shimahara, Y., Miki, Y.: Deep learning-based algorithm for lung cancer detection on chest radiographs using the segmentation method. Scientific Reports **12**(1), 727 (2022) https://doi.org/10.1038/s41598-021-04667-w

[11] Abdusalomov, A.B., Mukhiddinov, M., Whangbo, T.K.: Brain tumor detection based on deep learning approaches and magnetic resonance imaging. Cancers **15**(16), 4172 (2023) https://doi.org/10.3390/cancers15164172

[12] John, A., Nundy, K.K., Cardiff, B., John, D.: Somnnet: An spo_2-based deep learning network for sleep apnea detection in smartwatches. In: Proceedings of the 43rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Mexico, pp. 1961–1964 (2021). https://doi.org/10.1109/EMBC46164.2021.9631037

[13] Ansari, Y., Mourad, O., Qaraqe, K., Serpedin, E.: Deep learning for ecg arrhythmia detection and classification: An overview of progress for period 2017–2023. Frontiers in Physiology **14** (2023) https://doi.org/10.3389/fphys.2023.1246746

[14] Madan, P., Singh, V., Singh, D.P., Diwakar, M., Pant, B., Kishor, A.: A hybrid deep learning approach for ecg-based arrhythmia classification. Bioengineering **9**(4), 152 (2022) https://doi.org/10.3390/bioengineering9040152

[15] Moody, G.B., Mark, R.G.: The impact of the mit-bih arrhythmia database. IEEE Engineering in Medicine and Biology Magazine **20**(3), 45–50 (2001) https://doi.org/10.1109/51.932724

[16] Khan, M.M.R., Siddique, M.A.B., Sakib, S., Aziz, A., Tanzeem, A.K., Hossain, Z.: Electrocardiogram heartbeat classification using convolutional neural networks for the detection of cardiac arrhythmia. In: Proceedings of the 4th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud), Palladam, India, pp. 915–920 (2020). https://doi.org/10.1109/I-SMAC49090.2020.9243474

[17] Khan, F., Yu, X., Yuan, Z., Rehman, A.u.: Ecg classification using 1-d convolutional deep residual neural network. PLOS ONE **18**(4) (2023) https://doi.org/10.1371/journal.pone.0284791

[18] Rafi, S.M., Akthar, S.: Ecg classification using a hybrid deep learning approach. In: Proceedings of the International Conference on Artificial Intelligence and Smart Systems (ICAIS), Coimbatore, India, pp. 302–305 (2021). https://doi.org/10.1109/ICAIS50930.2021.9395897

[19] Analog Devices: AD8232: Single-Lead Heart Rate Monitor Front End – Data Sheet, Rev. 0 edn. Analog Devices, Norwood, MA, USA. Analog Devices. https://www.analog.com/media/en/technical-documentation/data-sheets/ad8232.pdf

[20] Marella, V.: Comparative analysis of container orchestration platforms: Kubernetes vs. docker swarm. International Journal of Scientific Research in Science and Technology **11**(5), 526–543 (2024) https://doi.org/10.32628/IJSRST24105254

[21] Vayghan, L.A., Saied, M.A., Toeroe, M., Khendek, F.: Kubernetes as an availability manager for microservice applications. arXiv preprint arXiv:1901.04946 (2019) https://doi.org/10.48550/arXiv.1901.04946

[22] Dey, R., Salem, F.M.: Gate-variants of gated recurrent unit (gru) neural networks. Technical report, Circuits, Systems, and Neural Networks (CSANN) Lab, Department of Electrical and Computer Engineering, Michigan State University, East Lansing, MI, USA. https://arxiv.org/pdf/1701.05923

[23] Cordonnier, J.-B., Loukas, A., Jaggi, M.: Multi-head attention: Collaborate instead of concatenate. arXiv preprint arXiv:2006.16362 (2021)

[24] ADS: ECG Simulator SIM II – Clinical, Hospital, Home, and Veterinary Use. https://www.indiamart.com/proddetail/ecg-simulator-sim-ii-8549354330.html

[25] Tran, K.D., Tang, L.H., Nguyen, U.D., Huynh, Q.T.: Developing a deep learning model using a combination of cnn and rcnn for cardiovascular disease classification. In: Proceedings of the 2024 International Conference on Advanced Technologies for Communications (ATC), Ho Chi Minh City, Vietnam, pp. 511–516 (2024). https://doi.org/10.1109/ATC63255.2024.10908251

[26] Moody, G.B., Mark, R.G.: MIT-BIH Arrhythmia Database. https://doi.org/10.13026/C2F305 . https://physionet.org/content/mitdb/1.0.0/