ATC-CNN-Based IoT Framework for Real-Time Cardiovascular Monitoring: A Comparative Analysis with Deep Learning Models

Dev Ras Pandey [1*], Ahilya Dubey [1]

Abstract

Background: Cardiovascular diseases (CVDs), including hypertension, coronary heart disease, and ventricular fibrillation, remain the leading cause of death worldwide. The COVID-19 pandemic accelerated the adoption of telecardiology to minimize in-person interactions, enhancing access to cardiovascular care, especially in remote areas. However, traditional real-time monitoring (RTM) systems often require patient visits, creating a need for cost-effective, user-friendly alternatives that leverage IoT and AI for improved patient management. Methods: This study developed an IoT-enabled RTM system integrated with an Adaptive Thresholding Classifier-Convolutional Neural Network (ATC-CNN) framework for managing cardiovascular patients (CP). Data from a heart failure dataset in the UCI Machine Learning Archive was used to train and evaluate the model. Multiple deep learning (DL) algorithms, including MLP, CNN, LSTM, RNN, and the proposed ATC-CNN, were assessed based on accuracy, precision, recall, and F1 scores. Results: The ATC-CNN model achieved an accuracy of 0.9831, outperforming other DL models, including MLP, CNN, LSTM, and RNN. It demonstrated superior capabilities in handling complex cardiovascular data, offering reliable and timely diagnosis with high precision and recall. The integration of IoT and AI facilitated continuous monitoring and real-time data analysis, addressing key limitations of traditional RTM systems. Conclusion: The ATC-CNN framework shows great potential for revolutionizing cardiovascular care by enhancing remote monitoring capabilities and clinical decision-making. It provides an effective, real-time solution for early diagnosis and intervention, particularly in remote and underserved areas. Future research should focus on expanding datasets and refining the model for broader adaptability in diverse healthcare settings.

Keywords: Cardiovascular diseases, Real-time monitoring, IoT, AI, ATC-CNN

Significance | This study determines the ATC-CNN's superior performance in real-time monitoring of cardiovascular patients revolutionizes care, enhancing access, accuracy, and clinical outcomes.

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Introduction

Cardiovascular diseases (CVDs), including hypertension, coronary heart disease, and ventricular fibrillation, remain the leading cause of death globally, affecting millions of lives each year (Giovanni et al., 2020). With the onset of the COVID-19 pandemic, cardiology, one of the most essential services in hospitals, underwent significant transformations as healthcare systems adapted to new challenges (Tanner et al., 2020). In particular, telemedicine, including telecardiology, gained prominence as hospitals were forced to minimize in-person interactions, prompting the development of teleconsultation frameworks to support outpatient care during the pandemic (Das et al., 2022). Telecardiology, a subfield of

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telemedicine that focuses on cardiovascular health, has emerged as a valuable tool for delivering timely care to remote and underserved populations, improving access to essential medical services (Majumder et al., 2023).

Telecardiology primarily relies on electrocardiograms (ECGs) as the standard diagnostic tool for assessing patients with cardiovascular conditions, such as rhythm disorders and conduction abnormalities (Lavanya et al., 2024; Molinari et al., 2018). Traditional 12-lead ECG devices use ten Ag/AgCl electrodes placed on the body to monitor the heart's electrical activity, serving as the cornerstone of cardiovascular diagnostics (Satish & Herald, 2024). While conventional real-time monitoring (RTM) systems, including peripheral cardiac activity recorders and Holter monitors, are available, these technologies often require patient visits to healthcare facilities, which can be cumbersome for those living in remote areas (Dahiya et al., 2024). Recent advancements have introduced wearable RTM systems that incorporate novel ECG acquisition technologies using less complex and non-invasive sensors; however, these systems are often limited to personal or entertainment purposes, restricting their clinical utility (Xu et al., 2019; Pani et al., 2015).

The development of cost-effective, user-friendly RTM systems that can streamline diagnostic processes without requiring patient travel remains a critical need in healthcare. This need is increasingly being addressed through the Internet of Things (IoT), which offers a promising framework for transforming cardiovascular care delivery (Seferagić et al., 2020). The IoT connects physical devices equipped with sensors to the internet, facilitating seamless data exchange and communication. In the context of healthcare, the IoT enables the continuous monitoring and analysis of patient data, thus revolutionizing patient management and enhancing the efficiency of healthcare systems (Camgözlü & Kutlu, 2023). By leveraging IoT, real-time data from medical devices can be collected, analyzed, and used to inform clinical decision-making, significantly improving the quality of care for cardiovascular patients (Birje & Hanji, 2020).

The integration of IoT in healthcare has given rise to the Internet of Medical Things (IoMT), an interconnected network of medical devices and systems that generate, collect, analyze, and transmit medical data (Bhuiyan et al., 2022). This connectivity has expanded the scope of RTM by enabling continuous patient monitoring both inside and outside traditional clinical settings, thus enhancing the ability of healthcare providers to respond to patients' needs in real time (Mumtaj Begum, 2022). For instance, wearable ECG devices can transmit data directly to healthcare providers, allowing for immediate assessment and intervention when abnormalities are detected (Bhuiyan et al., 2022). Additionally, AI technologies, particularly deep learning (DL), are increasingly integrated with IoT-enabled systems to enhance data processing and diagnostic accuracy (Lih et al., 2020; Ribeiro et al., 2020).

AI algorithms play a crucial role in managing the large volumes of data generated by IoT devices, offering personalized treatment recommendations and more precise diagnoses (Sumiati et al., 2024). The application of DL in automated ECG analysis, for example, allows for the rapid interpretation of complex cardiac signals, facilitating early detection of arrhythmias and other cardiac conditions (Ma et al., 2020). While early research employed machine learning techniques such as Convolutional Neural Networks (CNNs), Support Vector Machines, and fuzzy rough sets, current trends highlight a shift towards DL architectures, which offer advanced capabilities in handling non-linear and multidimensional data (Jothiramalingam et al., 2021; Sangaiah et al., 2020).

To optimize the performance of IoT-based RTM systems, a multi-tier architecture comprising edge, fog, and cloud computing layers is often employed (Surendar et al., 2024). The first layer, edge computing, processes data directly on the device, minimizing latency and reducing data transfer costs. The second layer, fog computing, provides intermediate processing capabilities, ensuring low latency and quick response times crucial for medical applications (Moghadas et al., 2020). Finally, cloud computing offers large-scale storage and complex data analytics, enabling more sophisticated AI-driven diagnostic support (Moghadas et al., 2020).

This study presents an innovative IoT-enabled RTM system for managing cardiovascular patients (CP), incorporating AI technologies to enhance decision-making through effective data management, storage, and collection. By integrating IoT and AI, the proposed system aims to address current gaps in cardiovascular care, particularly in remote and underserved communities, ultimately improving patient outcomes and reducing the burden on healthcare facilities.

2. Materials and Methods

This section outlines a healthcare system utilizing IoT technology tailored for the real-time monitoring (RTM) of cardiovascular patients (CP). The framework integrates artificial intelligence (AI), cloud computing services, and IoT technologies. Figure 1 depicts the proposed configuration for IoT-based RTM of CP, allowing medical professionals to efficiently monitor health in real time through IoT devices. This system uses cloud computing and IoT technologies to provide global access to health information for patients with cardiovascular diseases (CD) at any time.

Authentication and Security Protocols

The IoT-based smart medical system establishes security protocols using Zigbee authentication, which ensures secure data transfer between devices. An encryption key of 256 bits identifies the JSON file during data transmission. Real-time validation authenticates the gadget's identity by generating a token containing unique token requests and specific attributes. Authentication during RTM and

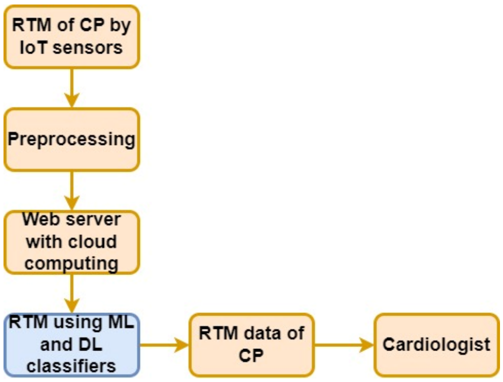

Figure 1. Proposed workflow of IoT-based RTM of CP

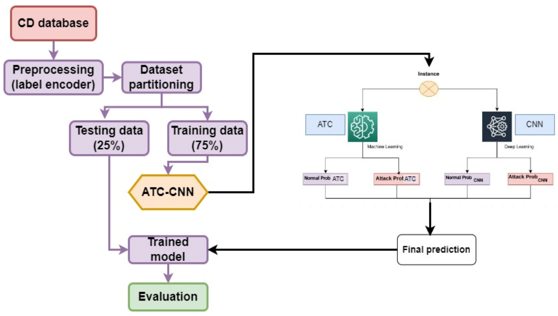

Figure 2. Proposed ATC-CNN for RTM of CP

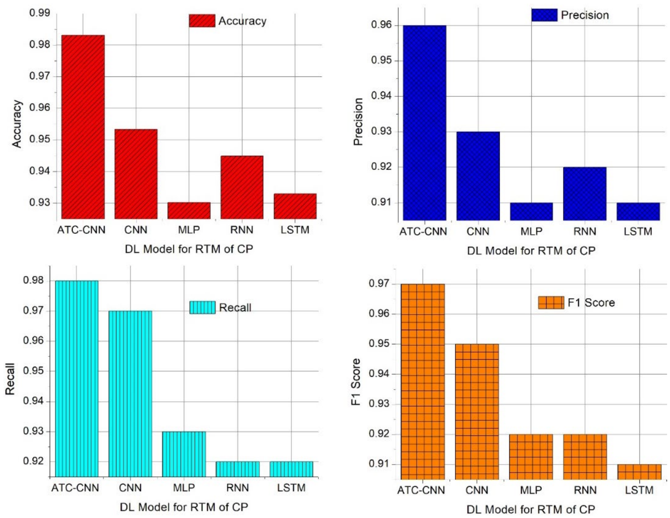

Figure 3. Performance analysis of various DL models for RTM of CP through the integration of IoT and AI.

data transfer is ensured through Firebase unique tokens and device-generated 256-bit identifiers, following Firebase's security regulations.

The authentication system operates through a three-step protocol:

Gadget Identifier: Confirms that the request originates from a specific device but does not contain personal information.

Customized Identifier: Contains all user data except personal information, ensuring security.

Token Authentication: A Firebase ID token encapsulates the user profile and confirms the bearer's authority. This token is valid for one hour and is irrevocable.

Figure 1 demonstrates how smart devices enable the transfer and updating of CP data within the IoT framework, ensuring real-time data accessibility. The equipment utilized is selected based on the CP treatment facility and hospital requirements, facilitating RTM of CP data and ensuring immediate access to urgent medical care for patients (Figure 1) (Birje & Hanji, 2020). Cloud storage allows physicians to access data remotely, providing guidance based on the patient's condition.

System Configuration

The primary aim of this smart system is to improve patient survival rates by providing an economical, reliable, and easy-to-use RTM solution for CD. The system collects data from multiple sources, sending it to the Cloud for analysis using deep learning (DL) and machine learning (ML) models. This setup allows medical professionals to access well-organized data, promoting extensive research and evaluation.

Database

The study utilizes a heart failure dataset from the UCI Machine Learning (UCI-ML) archive, focusing on patients with severe heart failure. The dataset includes 12 clinical characteristics recorded during monitoring. Out of 301 records, 195 correspond to male CPs and 106 to female CPs .

Deep Learning Model

DL has emerged as a critical component of AI research, showing promising results in healthcare data analysis and visualization. The use of DL techniques allows for automated, efficient, and accurate diagnosis without manual feature extraction, making it a preferred method in healthcare.

This study introduces an efficient model for RTM of CP using a combined ML-DL approach called the ATC-CNN architecture, depicted in Figure 2. This framework features hidden input and output layers, with the hidden layer functioning as the processing core, establishing connections between inputs and outputs. Performance assessments of multi-layer structures reveal that hidden-layer configurations produce favorable outcomes. The hidden layer architecture provides input attributes derived from the cardiac failure database, with parameters including an initial learning rate of 0.01, a batch size of 128, an error rate of 0.25, and 20 iterations. The CNN-based methodology applied here utilizes a total of eight layers, tested for their effectiveness in RTM of CP.

Model Training

In the initial phase, the heart failure dataset served as the input, with 12 CP-specific features selected for training to enhance RTM accuracy. Early and precise evaluation of CP patients experiencing sudden cardiac arrest is vital for improving survival rates. Voting classifiers (VC) are used to aggregate the results of multiple classifiers, arriving at a final decision through a voting mechanism. VCs are divided into soft and hard VCs, with soft voting calculating percentage weights for each classifier and hard voting determining outcomes based on classifier predictions.

This study employs a combination of VC, ATC, and CNN models, outperforming alternative RTM methods for CP. Figure 2 illustrates the development process of the proposed VC, emphasizing its enhanced capabilities in real-time monitoring of cardiovascular conditions.

The proposed system effectively integrates IoT and AI technologies, demonstrating the potential for revolutionizing CP management by ensuring prompt and precise diagnostics, improving patient outcomes through continuous monitoring and personalized care.

$$\hat{L} = argmax\{\textstyle\sum_i^n ATC_{i,} \sum_i^n CNN_{i,}\} \quad (1)$$

where $\sum_i^n ATC_{i,}$ and $\sum_i^n CNN_{i,}$ monitor the likelihood-based outcomes for every test sample by ATC and CNN, respectively. The probabilities of the ATC and CNN instances are evaluated against VC criteria.

3. Results and Discussion

The effectiveness of the ATC-CNN-based framework was evaluated using a database containing data from cardiovascular patients (CP). The performance of the ATC-CNN model was compared with other deep learning (DL) algorithms, including Multi-layer Perceptron (MLP), Convolutional Neural Network (CNN), Long Short Term Memory (LSTM), and Recurrent Neural Network (RNN). All models were trained and tested using a 75:25 ratio, utilizing Python libraries such as Keras and TensorFlow.

Performance Evaluation of DL Models

Figure 3 illustrates the performance analysis of various DL models for RTM of CP through IoT and AI integration. Among the models tested, the ATC-CNN approach demonstrated outstanding performance, achieving an accuracy of 0.9831, which surpassed other models such as MLP, RNN, and LSTM. The ATC-CNN's high accuracy highlights its superior capacity to handle complex data, making it the most effective model for real-time monitoring of CP. The RNN model followed the ATC-CNN, attaining an accuracy score of 0.9399. However, it lagged behind the ATC-CNN in key metrics such as precision, recall, and F1 score, suggesting that while RNNs can manage sequential data well, they were less effective than the ATC-CNN in this context. MLP and LSTM models, although performing adequately, did not match the precision or recall of the ATC-CNN, indicating limitations in handling the intricate, high-dimensional data associated with cardiovascular monitoring.

Comparative Analysis with Existing Models

The proposed ATC-CNN model excelled across all key metrics compared to traditional DL models. The precision, recall, and F1 scores of the ATC-CNN were significantly higher than those of other models, confirming its effectiveness in accurately classifying cardiovascular conditions. The CNN model within the ATC-CNN framework significantly contributed to this superior performance due to its strong feature extraction capabilities, which enabled better identification of critical patterns in the cardiovascular data.

The high recall score of 0.982 achieved by the ATC-CNN model underscores its reliability in identifying true positives, minimizing the risk of misdiagnosing critical conditions in CP patients. This is particularly important in real-time monitoring scenarios where missed diagnoses can have severe consequences. Furthermore, the precision score demonstrates the model's ability to minimize false positives, ensuring that interventions are only recommended when truly necessary.

Advantages of the ATC-CNN Approach

The integration of IoT and AI technologies in the proposed system addresses several critical challenges in cardiovascular care. Traditional RTM systems often require patients to visit healthcare facilities, limiting access for individuals in remote areas. By leveraging the ATC-CNN framework, healthcare providers can continuously monitor patients' conditions in real time, offering immediate responses when necessary. This approach not only improves access to care but also reduces the burden on healthcare systems, especially in the context of the ongoing need for remote health solutions like telecardiology.

The ATC-CNN model's architecture, which combines a Voting Classifier (VC) with CNN layers, enhances its predictive accuracy by integrating multiple classifier outputs. The VC aggregates decisions from different models, providing a robust and balanced approach to classification. This multi-layered approach improves the reliability and scalability of the system, making it adaptable to various clinical settings and capable of handling large, complex datasets.

Implications for Clinical Practice

The proposed IoT-enabled RTM system can revolutionize cardiovascular patient management, offering a cost-effective and efficient solution that aligns with current trends in telemedicine and AI integration in healthcare. The system's ability to provide accurate, real-time data analysis supports clinical decision-making, ensuring timely interventions that can significantly improve patient outcomes.

Moreover, this framework supports extensive research and data evaluation, contributing to a deeper understanding of cardiovascular conditions. By continuously gathering and analyzing data, healthcare providers can develop personalized treatment plans, enhancing the quality of care and potentially reducing mortality rates associated with cardiovascular diseases.

Limitations and Future Directions

While the ATC-CNN model has shown promising results, some limitations should be considered. The model’s performance relies heavily on the quality and quantity of data available, which may vary across different clinical settings. Future research should focus on expanding the dataset and incorporating diverse patient populations to enhance the generalizability of the model. Additionally, integrating more advanced DL techniques, such as hybrid models that combine CNNs with other architectures like Graph Neural Networks, could further improve diagnostic accuracy.

Further exploration of real-world implementation challenges, including data privacy concerns and system integration within existing healthcare infrastructures, is also necessary. Addressing these issues will be crucial in translating the success of the ATC-CNN framework from research settings into practical clinical applications.

4. Conclusion

The proposed ATC-CNN-based framework effectively integrates IoT and AI technologies for real-time monitoring of cardiovascular patients. Compared to other deep learning models such as MLP, CNN, LSTM, and RNN, the ATC-CNN demonstrated superior performance, achieving an accuracy of 0.9831. This highlights its potential as a robust tool for the continuous monitoring of cardiovascular conditions, addressing key challenges in traditional RTM systems that often require in-person visits to healthcare facilities. The integration of IoT allows for seamless data collection and analysis, significantly improving access to timely care, especially for remote and underserved populations. The ATC-CNN’s high precision, recall, and F1 scores underscore its reliability in clinical settings, enhancing patient management by facilitating early diagnosis and intervention. Future research should focus on expanding datasets and refining the model to further enhance its adaptability and accuracy in diverse healthcare environments.

Author contributions

DRP* and AD contributed to conceptualization, fieldwork, data analysis, drafting the original manuscript, editing, funding acquisition, and manuscript review. Both DRP and AD were involved in research design, methodology validation, data analysis, visualization, and manuscript review and editing. Additionally, DRP took the lead in methodology validation, investigation,

funding acquisition, supervision, and final revisions. All authors have reviewed and approved the final version of the manuscript.

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Competing financial interests

The authors have no conflict of interest.

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