Pertanika Proceedings 1 (5): 55 - 59 (2025)

PERTANIKA PROCEEDINGS

Journal homepage: http://www.pertanika.upm.edu.my/

Enhancing Arrhythmia Detection and Classification: Leveraging Lightweight CNN and ResNet Models

K. Ghamya and K. Reddy Madhavi*

School of Computing, Mohan Babu University, Tirupati, Andhra Pradesh 517102, India

ABSTRACT

Cardiovascular diseases, especially arrhythmias, continue to be the most common cause of death worldwide, and accurate and efficient diagnostic tools are thus in high demand. This work presents a new approach for arrhythmia classification using deep learning with two models: a lightweight CNN optimized for computational efficiency and a ResNet-based model optimized for higher accuracy. The models were trained and tested on the MIT-BIH Arrhythmia Dataset with raw ECG signals pre-processed using noise reduction, normalization, and segmentation. The lightweight CNN proved to be a good candidate for real-time applications because of its speed and efficiency, while the ResNet model performed well in terms of precision and recall, making it suitable for clinical diagnostics. This work contributes to the design of scalable and effective diagnostic tools for the detection of arrhythmia, enhancing the outcome of healthcare and providing early intervention strategies, through the research conducted based on trade-off between computational cost and classification accuracy.

Keywords: Arrhythmia classification, CNN, ResNet, deep learning, ECG signal processing, medical diagnostics

INTRODUCTION

Cardiovascular diseases rank among the leading causes of death globally. Within this group, arrhythmias defined by irregular heart rhythms, constitute a major share. Accurate and early diagnosis of arrhythmias can ensure timely intervention, thus avoiding major complications such as stroke, heart failure, or sudden cardiac arrest (Daydulo, 2023). Traditionally, arrhythmias are diagnosed using Electrocardiograms (ECGs), which record the electrical activity of the heart. However, manual interpretation of ECGs is time-consuming, prone to errors, and requires specific expertise, which often poses challenges in the timely or accurate assessment, especially in resource-poor settings (Bai et al. 2024).

ARTICLE INFO

Article history:
Received: 29 August 2025
Published: 31 October 2025

DOI: https://doi.org/10.47836/pp.1.5.011

E-mail addresses:
ghamyakotapati@gmail.com (K. Ghamya)
kreddymadhavi@gmail.com (K. Reddy Madhavi)
* Corresponding author

e-ISSN: 3083-9475

Recent advances in deep learning and machine learning have demonstrated remarkable potential for the automatic processing of medical data, including ECG signals (Wu & Guo, 2025). Convolutional Neural Networks (CNNs) are highly successful in extracting subtle patterns from ECG waveforms to classify arrhythmias with high accuracy (Jeong et al. 2021 & Xiao et al., 2023). Other architectures, such as Residual Networks (ResNet), can be utilized to avoid the vanishing gradient problem in deep networks by adopting skip connections and training very accurate models (He et al., 2016). This work suggests the construction and assessment of two deep learning arrhythmia classifiers. One is a low-resource CNN aimed for efficiency and real-time purposes (An et al., 2024), and the other is a ResNet-variant optimized for enhanced classification performance. These two were trained and evaluated using the MIT-BIH Arrhythmia Dataset, commonly employed in the context of ECG signal classification (Moody & Mark, 2001).

PROBLEM STATEMENT

The implementation of arrhythmia detection in wearables and apps is confronted by the challenge of computational efficiency at the expense of accuracy and compatibility for deployment within resource-limited environment. Addressing the challenges is essential to achieving significant detection improvement. In this study, it includes two architectures of deep learning: the former is lightweight CNN for deployment that is efficient on resources and the latter ResNet-based for accuracy at a level of state of the art. The main work is developed from evaluating models against the MIT-BIH Arrhythmia Dataset by focusing preprocessing techniques to ensure higher quality in the data for making scalable, accurate, and interpretable systems in arrhythmia detection.

METHODOLOGY

Figure 1 depicts a dual-model approach towards arrhythmia classification, capitalizing on the benefits of both lightweight and deep architectures. The workflow begins with the preprocessing of input dataset and then applies two proposed models: a lightweight Convolutional Neural Network architecture and a ResNet-based architecture. They are built to bridge the gap between computational efficiency and classification accuracy for this application. These models aim to improve real-time diagnostic capabilities while maintaining precision and recall, hence ensuring suitability across diverse applicationsfrom wearable devices to clinical settings.

Lightweight CNN

Figure 2 depicts the architecture overview of lightweight CNN which is optimized for resource-constrained environments, such as wearable devices and mobile applications, the

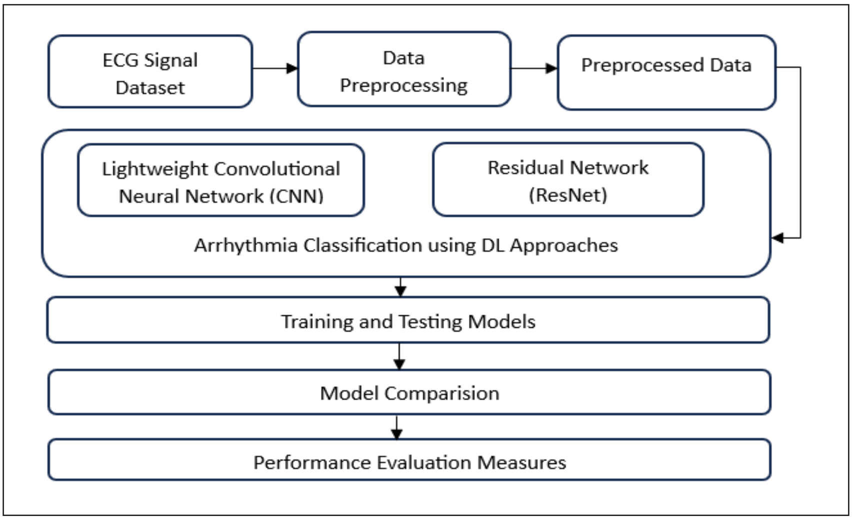

Figure 1. An overview of a DL-based approach for arrhythmia classification

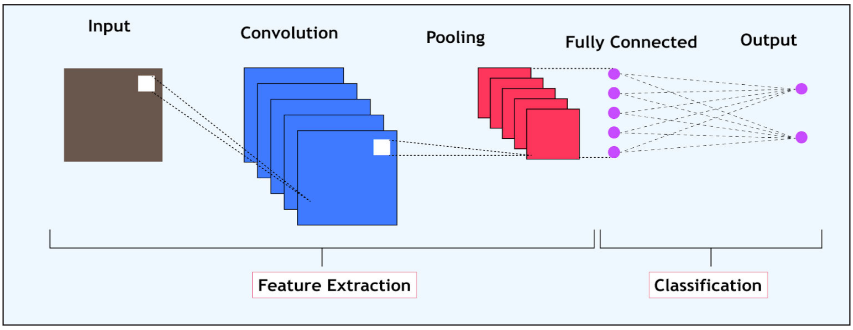

Figure 2. Lightweight CNN architecture

lightweight CNN is built to achieve fast inference with minimal computational overhead, making it suitable for real-time arrhythmia detection.

ResNet-Based Model

The Figure 3 depicts the architecture overview of ResNet-Based model which enable the model to overcome challenges of training deep networks, vanishing gradients being one of the primary issues which affect feature extraction.

RESULTS AND DISCUSSION

The dataset comprises 48 half-hour recordings of ECG signals, annotated with 16 arrhythmia classes. In this study, 70% of the dataset (balanced across classes) was used as the training set, 15% of dataset was assigned as a validation set for hyperparameter tuning and the

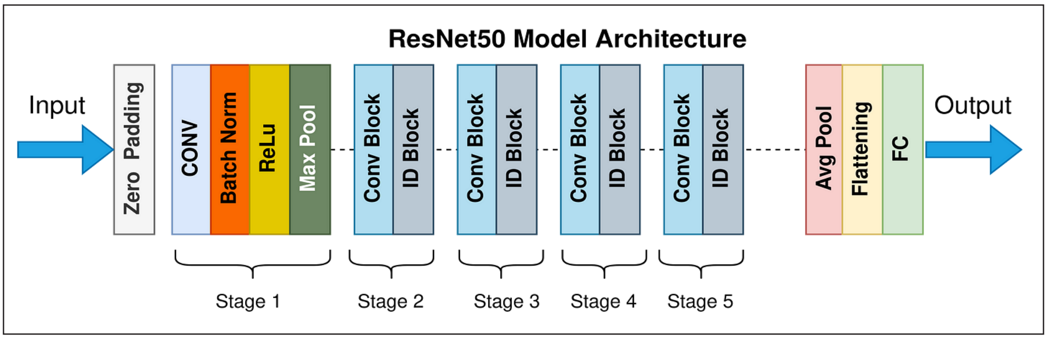

Figure 3. ResNet architecture

remaining 15% of dataset was allocated as a test set for final evaluation. To address the class imbalance in the dataset, data augmentation techniques such as random oversampling technique were employed. The models were evaluated using accuracy, precision, recall, F1-score, and inference time. The results are summarized in Table 1.

Table 1 shows the ResNet-based model outperformed the lightweight CNN and other models in accuracy, precision, recall, and F1-score, making it suitable for high-stakes clinical applications. The lightweight CNN achieved faster inference times compared to other models, demonstrating its suitability for real-time arrhythmia monitoring in resource-constrained environments.

Table 1
Comparison of performance metrics with other models

Metric	Lightweight CNN Model	ResNet-based Model	Traditional CNN Model	LSTM-based Model	Hybrid CNN-LSTM Model
Accuracy	91.4%	95.6%	87.2%	88.5%	89.3%
Precision	89.7%	94.2%	85.0%	86.2%	87.5%
Recall	90.1%	95.1%	84.3%	87.1%	88.0%
F1-Score	89.9%	94.6%	84.6%	86.6%	87.7%
Inference Time(ms)	1.2 ms	12.8 ms	15.6 ms	25.4 ms	18.3 ms

CONCLUSION

This study demonstrated the potential of deep learning models in arrhythmia classification, balancing the trade-off between computational efficiency and diagnostic accuracy. The lightweight CNN offered a viable solution for real-time monitoring scenarios, while the ResNet model provided high-performance classification suitable for clinical use. Together, these models contributed to the advancement of scalable and effective tools for early detection and management of cardiovascular conditions, ultimately supporting improved patient outcomes.

ACKNOWLEDGEMENT

The authors sincerely thank the organizers of the conference for providing the opportunity to present the research project and thank for their valuable support throughout the event. The conference served as an excellent platform to exchange ideas, gain insights, and interact with distinguished researchers and professionals.

REFERENCES

An, X., Shi, S., Wang, Q., Yu, Y., & Liu, Q. (2024). Research on a lightweight arrhythmia classification model based on knowledge distillation for wearable single-lead ECG monitoring systems. *Sensors, 24(24)*, Article 7896. https://doi.org/10.3390/s24247896

Bai, X., Dong, X., Li, Y., Liu, R., & Zhang, H. (2024). A hybrid deep learning network for automatic diagnosis of cardiac arrhythmia based on 12-lead ECG. *Scientific Reports, 14*, Article 24441. https://doi.org/10.1038/s41598-024-75531-w

Daydulo, Y. D., Thamineni, B. L., & Dawud, A. A. (2023). Cardiac arrhythmia detection using deep learning approach and time–frequency representation of ECG signals. *BMC Medical Informatics and Decision Making, 23*, Article 232. https://doi.org/10.1186/s12911-023-02326-w

He, K., Zhang, X., Ren, S., & Sun, J. (2021). He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 770-778. https://doi.org/10.1109/CVPR.2016.90.

Jeong, D. U., & Lim, K. M. (2021). Convolutional neural network for classification of eight types of arrhythmia using 2D time–frequency feature map from standard 12-lead electrocardiogram. *Scientific Reports, 11,* Article 20396. https://doi.org/10.1038/s41598-021-99975-6

Moody, G. B., & Mark, R. G. (2001). The impact of the MIT-BIH Arrhythmia Database. *IEEE Engineering in Medicine and Biology Magazine, 20*(3), 45–50. https://doi.org/10.1109/51.932724

Wu, Z., & Guo, C. (2025). Deep learning and electrocardiography: systematic review of current techniques in cardiovascular disease diagnosis and management. *BioMedical Engineering OnLine, 24*, Article 23. https://doi.org/10.1186/s12938-025-01349-wA

Xiao, Q., Lee, K., Mokhtar, S. A., Ismail, I., Md Pauzi, A. L., Zhang, Q., & Lim, P. Y. (2023). Deep learning-based ECG arrhythmia classification: A systematic review. *Applied Sciences, 13*(8), Article 4964. https://doi.org/10.3390/app13084964