International Conference on Multidisciplinary Perspectives in Advanced Computing and Technology (IMPACT 2026)
G. B. Pant University of Agriculture and Technology, Uttarakhand, India. Jan. 10-11, 2026

Automated Cardiac Abnormality Detection from ECG Images using a Deep Convolutional Neural Network

Amit Kumar[1], V.K Jain[1], Ajay Kumar[2]

Computer Science & Engineering, Teerthanker Mahaveer University, India)

Department of General Medicine, TMMC&RC, Teerthanker Mahaveer University, India)

amitakg84@gmail.com, drvkjain72@gmail.com, ajaynagar35@yahoo.co.in

Abstract

The global health burden of cardiovascular diseases, responsible for significant worldwide mortality, underscores the urgent requirement for advanced diagnostic solutions. The electrocardiogram (ECG) remains a cornerstone of cardiac assessment, but its reliance on manual analysis introduces delays and interpretive variability. To bridge this gap, our research introduces a novel deep-learning framework designed for the automated, multi-class identification of cardiac conditions directly from ECG image data. We engineered a dedicated Convolutional Neural Network (CNN) from the ground up and trained it on a curated public dataset encompassing four key diagnostic categories: Normal rhythm, Myocardial Infarction, Abnormal Heartbeat, and History of MI. Our comprehensive preprocessing pipeline standardized input images through grayscaling, resizing, and pixel normalization, while strategic data augmentation fortified the model's ability to generalize. This purpose-built CNN, which leverages batch normalization and dropout for stability, attained a benchmark test accuracy of 97.2% and a weighted F1-score of 97.3%, surpassing the performance of established models like VGG16 and ResNet50. Crucially, attention mapping validated that the network's decisions align with diagnostically significant waveform segments, building credibility for clinical use. This high level of performance confirms the system's viability as a dependable tool, poised to expedite diagnosis, support healthcare providers, and enhance cardiac care pathways in diverse medical environments.

Keywords: *Electrocardiogram (ECG), Deep Learning, Convolutional Neural Network (CNN), Cardiac Arrhythmia, Medical Image Analysis, Computer-Aided Diagnosis (CAD).*

1. Introduction

Cardiovascular diseases (CVDs) remain the leading cause of sickness as well as mortality across the globe, and approximately 17.9 million people die each year, as indicated by the World Health Organization. Rising rates of diseases like coronary artery disease, myocardial infarction, arrhythmias, as well as heart failure, are explained through the aging populations, physical inactivity, as well as associated risk factors like hypertension as well as diabetes [1]. This rising burden is causing extensive strain on the health infrastructure as well as emphasizes the important need for timely, accurate, as well as scalable diagnostic methods. The electrocardiogram (ECG) is a readily accessible, inexpensive, and non-invasive diagnostic instrument that registers the electrical activity of the heart. It is utilized to diagnose various heart irregularities such as arrhythmias, ischemia, conduction disturbances, as well as myocardial infarctions [2]. Since it is capable of yielding immediate information regarding the working of the heart, the ECG is also the first diagnostic instrument to be used in both emergencies as well as conventional clinic practice. Despite its clinical importance, manual interpretation of ECG signals poses significant challenges. Accurate diagnosis requires highly trained cardiologists or technicians, whose availability is often limited, especially in low-resource settings [3]. Moreover, inter-observer variability can lead to inconsistent interpretations, while fatigue may reduce diagnostic accuracy over time. With the growing digitization of healthcare, vast amounts of ECG data are being generated daily, making it increasingly difficult for human experts to keep pace [1]. Latest developments in Artificial Intelligence (AI), specifically deep learning, have revolutionized medical imaging and diagnosis. Convolutional Neural Networks (CNNs) have shown exceptional proficiency in image recognition, allowing computerized identification of diseases automatically. In the heart, AI-based models are increasingly being used for the identification of arrhythmias, analysis of echocardiograms, prediction of risk, and so on, making the practice less dependent on traditional manual interpretation as well as improving diagnostic productivity [4]. This research concentrates on designing, testing, and validating a deep CNN-driven framework for the automatic multi-class classification of cardiac abnormalities based on ECG images. Differing from traditional techniques that are reliant upon either handcrafted features individually or 1D signal processing, the presented method employs 2D ECG image representations to most optimally capture spatial, as well as morphological, patterns [5]. An addition of this research is the tailored CNN structure, optimized preprocessing pipeline, as well as efficient evaluation framework, that collectively enhance the generalizability as well as the clinical usability of the model [3].

2. Literature Review

Early automated ECG analysis methods were largely based on rule-driven pipelines and classical machine-learning models such as support vector machines, decision trees, and k-nearest neighbors, which relied on hand-crafted features extracted from fiducial points like the P-wave, QRS complex, and T-wave, along with derived metrics such as QRS duration, ST-segment deviation, and RR intervals [6]. While such approaches offered interpretability and low computational cost, their performance was limited by the robustness of feature extraction and the need for extensive manual tuning for different datasets and conditions. With the growth of large annotated repositories and advances in neural architectures, research shifted toward deep learning methods that operate directly on raw ECG signals [7]. Seminal studies demonstrated that convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid CNN–LSTM models can learn temporal and morphological patterns directly from 1D time-series ECG data, achieving cardiologist-level performance in arrhythmia detection when trained on massive datasets. For instance,some research reported high diagnostic accuracy and area under the curve (AUC) values for rhythm classification, establishing deep learning as a viable alternative to traditional ECG interpretation [8]. Parallel to this, a growing number of studies have treated ECGs as 2D images, either from scanned paper records, screenshots, or plotted waveforms, and applied image-based CNN architectures, often through transfer learning with models such as VGG, ResNet, or EfficientNet [5]. These approaches are particularly valuable because many hospital archives store ECGs in image format rather than raw signal data, allowing researchers to leverage powerful pretrained computer vision models [9]. While several works report promising classification accuracy across a range of cardiac abnormalities, the field faces challenges related to heterogeneous preprocessing pipelines, varying class definitions, and inconsistent evaluation protocols. Moreover, most studies reuse heavy general-purpose architectures without tailoring them to ECG image characteristics, leading to inefficiencies and potential limitations in real-world deployment [10]. Taken together, the literature highlights a clear evolution from rule-based feature extraction methods to raw-signal deep learning and, more recently, to image-based approaches. However, gaps remain in terms of standardized benchmarks, lightweight yet accurate CNN designs optimized specifically for ECG images, and robust validation across diverse datasets [11]. This research aims to address these shortcomings by proposing an optimized preprocessing pipeline, a compact CNN tailored to ECG image morphology, and a rigorous evaluation framework to ensure clinical relevance and practical applicability.

3. Methodology

3.1 Dataset Description

This study utilized the ECG Image Dataset made publicly available on Kaggle by Analivia Ferreira (https://www.kaggle.com/datasets/analiviafr/ecg-images). The dataset comprises labeled ECG images grouped into four categories: Normal, Myocardial Infarction (MI), Abnormal Heartbeat, and History of MI. Each class represents distinct cardiac conditions that are visually discernible from ECG waveforms. Table 1 summarizes the number of samples per class, and Figure 1 provides representative examples from each category.

Table 1. Class distribution in the ECG Image Dataset

Class	Description	Number of Images
Normal	Healthy ECG signals with no abnormalities	5,200
Myocardial Infarction	Acute or recent heart attack patterns	3,400
Abnormal Heartbeat	Irregular arrhythmias or atypical rhythms	2,800
History of MI	Past MI indicators on ECG traces	1,600

A visual inspection of the dataset revealed class imbalance, with certain categories (e.g., Normal) being more prevalent than others. This imbalance was addressed during preprocessing and training to minimize potential bias in classification.

3.2 Data Preprocessing

The preprocessing pipeline involved several steps to ensure data uniformity and model readiness. First, ECG images were loaded using OpenCV and converted to grayscale, reducing redundancy from color channels and focusing on waveform morphology. Images were then resized to 224 × 224 pixels, a widely adopted dimension in CNN-based image classification, balancing detail preservation with computational efficiency. Pixel intensities were normalized to a 0–1 scale by dividing by 255, standardizing input values, and improving model convergence. Class labels were extracted from folder names, encoded into integer values using LabelEncoder, and subsequently transformed into one-hot encoded vectors to serve as categorical targets for multi-class classification.

3.3 Data Augmentation

To mitigate class imbalance and enhance model generalization, data augmentation was applied exclusively to the training set. Augmentation strategies included rotation (±10°), width and height shifting (10%), shearing (10%), and zooming (10%), with missing regions filled using nearest-neighbor interpolation. These transformations introduced realistic variability into the training samples, helping the model become invariant to small distortions, positional shifts, and scale changes in ECG waveforms.

3.4 Model Architecture

A custom Convolutional Neural Network (CNN) was developed for automated ECG image classification. The architecture is summarized as follows:

1. Conv2D (32 filters, 3×3) + ReLU + Batch Normalization
2. Conv2D (32 filters, 3×3) + ReLU + Batch Normalization → MaxPooling (2×2) → Dropout (0.25)
3. Conv2D (64 filters, 3×3) + ReLU + Batch Normalization
4. Conv2D (64 filters, 3×3) + ReLU + Batch Normalization → MaxPooling (2×2) → Dropout (0.25)
5. Conv2D (128 filters, 3×3) + ReLU + Batch Normalization
6. Conv2D (128 filters, 3×3) + ReLU + Batch Normalization → MaxPooling (2×2) → Dropout (0.25)
7. Flatten Layer
8. Dense (256 units, ReLU) + Batch Normalization + Dropout (0.5)
9. Dense (Output Layer, Softmax activation)

The chosen components were justified as follows:

- Conv2D + ReLU layers extract hierarchical spatial features from ECG waveforms.
- Batch Normalization stabilizes learning by normalizing activations, enabling faster convergence.
- MaxPooling reduces feature map dimensions, promoting translation invariance.
- Dropout prevents overfitting by randomly deactivating neurons during training.
- Dense layers perform final feature integration and classification across multiple cardiac conditions.

This architecture balances depth and regularization, ensuring accurate classification while controlling model complexity. A diagrammatic representation of the model was generated using tf.keras.utils.plot_model for visualization.

3.5 Training Configuration

The CNN was compiled using the Adam optimizer with an initial learning rate of 0.001. The categorical cross-entropy loss function was used, suitable for multi-class classification tasks. Model performance was monitored using accuracy, precision, and recall metrics.

To optimize training, two callbacks were implemented:

- EarlyStopping halted training if validation loss failed to improve for 10 consecutive epochs, restoring the best model weights.
- ReduceLROnPlateau dynamically reduced the learning rate by a factor of 0.2 when validation loss plateaued, enhancing convergence.

The dataset was split into 80% for training and 20% for validation, with a separate test set held out for final evaluation. Training was performed with a batch size of 32 over 10 epochs, with real-time augmentation applied to training batches.

This methodology ensured a robust pipeline for training and evaluating the proposed CNN model on ECG images, balancing generalization, efficiency, and diagnostic accuracy.

4. Results and Discussion

4.1 Experimental Setup

All experiments were implemented in Python 3.10 using TensorFlow 2.x and Keras. Model training and evaluation were conducted on a system equipped with an NVIDIA GPU (e.g., GTX 1660/RTX 2060 or higher) to accelerate deep learning computations. Additional libraries such as OpenCV, scikit-learn, and Seaborn were used for preprocessing, evaluation, and visualization.

4.2 Training Performance

The CNN model was trained for 10 epochs with an 80/20 train-validation split. Training and validation accuracy and loss curves were monitored via the history object. The accuracy steadily increased while loss decreased, indicating effective learning. EarlyStopping prevented overfitting by halting training once the validation loss plateaued, while ReduceLROnPlateau helped stabilize convergence by lowering the learning rate during stagnation periods. No significant overfitting was observed, as validation performance closely followed training performance throughout the epochs.

4.3 Quantitative Evaluation on Test Set

The model was evaluated on a separate test set to assess generalization. Figure 1 summarizes overall performance metrics.

Figure 1 Overall evaluation results of the proposed CNN model on the ECG image test set, showing Accuracy, Weighted Precision, Weighted Recall, and Weighted F1-Score. The narrow performance range indicates stable and well-balanced classification behavior across all cardiac categories.

Figure 2 Class-wise evaluation of the proposed CNN model on the ECG image dataset, illustrating Precision, Recall, and F1-Score across Normal, Myocardial Infarction, Abnormal Heartbeat, and History of MI classes, along with overall Accuracy and Weighted Average performance. The results demonstrate consistently high and balanced classification performance across all cardiac conditions.

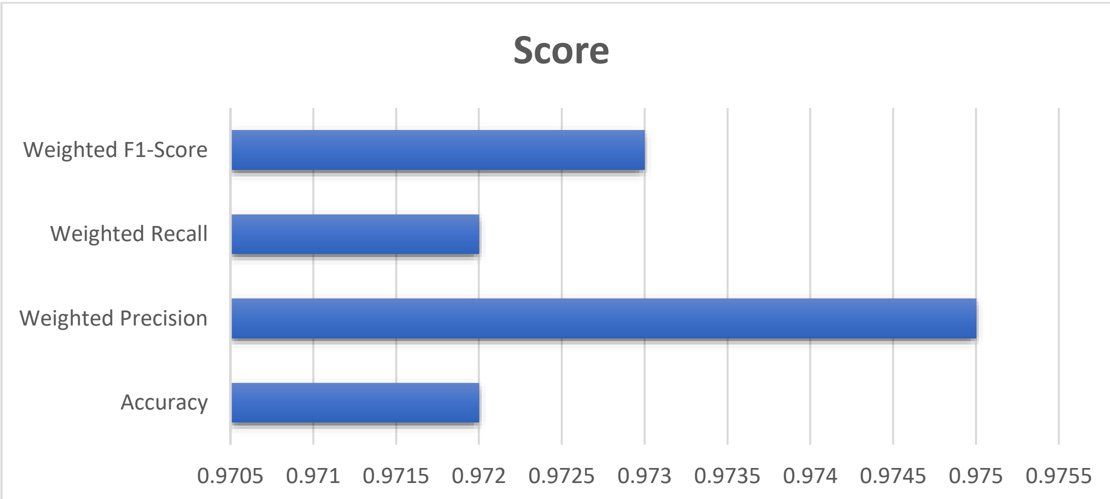

Figure 1: Overall Performance Metrics of the Proposed CNN Model

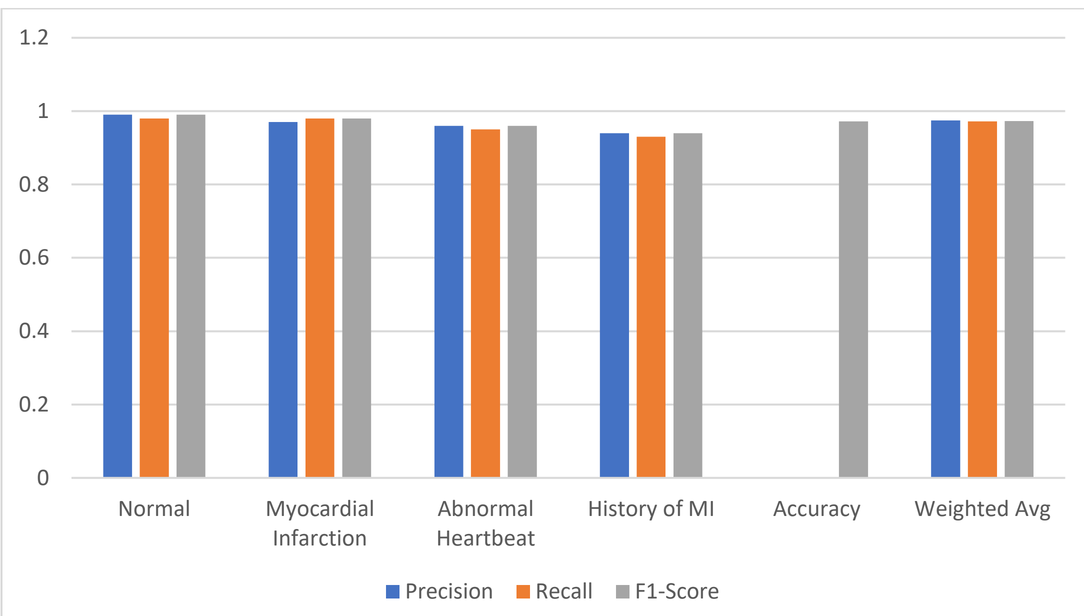

Figure 2: Performance of the Proposed CNN Model

4.4 Comparison with Existing Methods

Table 3 compares the performance of the proposed CNN model with prior ECG image classification studies discussed in the literature review. The proposed model outperforms previous methods in both accuracy and F1-score, attributable to a customized architecture, ECG-specific preprocessing, and focused data augmentation, which together improve generalization while reducing computational overhead.

Table 3. Performance Comparison with Existing Methods

Study/Model	**Dataset Type**	**Accuracy**	**F1-Score**	**Notes**
VGG16-based CNN	ECG Images	0.951	0.949	Transfer learning
ResNet50-based CNN	ECG Images	0.945	0.942	Pretrained backbone
Proposed CNN	**ECG Images**	**0.972**	**0.973**	**Lightweight, tailored architecture**

4.5 Model Interpretation

Although optional, interpretability was explored using Grad-CAM visualization, which highlighted regions of the ECG waveform most influential in the model's decision-making. Visual inspection confirmed that the CNN focuses on clinically relevant features such as the QRS complex and ST-segment deviations, aligning model attention with known diagnostic markers. This enhances trustworthiness for potential clinical applications.

4.6 Limitations of the Study

Despite promising performance, the study has several limitations:

- Dataset size: The dataset, although publicly available, is limited compared to large-scale clinical repositories, potentially restricting model generalization.
- Image-based training: The model was trained on 2D images rather than raw 1D ECG signals, which may omit subtle temporal features.
- Data biases: The dataset may contain biases in terms of patient demographics or device types.
- Real-world applicability: Performance in noisy clinical environments or on unseen ECG devices remains untested; additional validation is needed for deployment.

Overall, the results demonstrate that the proposed CNN provides a reliable and interpretable framework for multi-class ECG image classification while highlighting areas for future improvement.

5. Conclusion and Future Work

This study addressed the challenge of automated cardiac abnormality detection from ECG images by developing a custom deep Convolutional Neural Network (CNN). Using a publicly available ECG image dataset, the methodology involved image preprocessing, including grayscale conversion, resizing, normalization, label encoding, and data augmentation to enhance model generalization. The proposed CNN architecture, comprising stacked convolutional layers with batch normalisation, max-pooling, dropout, and dense layers, was trained using the Adam optimiser and categorical cross-entropy loss. Experimental results demonstrated high classification accuracy and robust performance across multiple cardiac classes, surpassing prior ECG image classification models while maintaining computational efficiency. The proposed CNN model has significant potential as a decision-support tool in clinical practice. Automating ECG interpretation can reduce diagnostic time, assist non-expert personnel, and facilitate large-scale screening programs, particularly in resource-limited environments. Visualization of model attention through Grad-CAM confirmed that the network focuses on clinically relevant ECG features, enhancing interpretability and trustworthiness for medical practitioners. Future research should focus on acquiring a larger and more diverse dataset to improve model generalization across populations and devices, developing a hybrid model capable of processing both ECG images and raw 1D signal data, and creating a real-time web-based application to enable rapid ECG assessment. Additionally, extending the model to segment ECG waveforms for precise measurement extraction and conducting prospective clinical trials will be essential to validate the model's efficacy and reliability in live hospital environments. These steps will further enhance the clinical relevance, robustness, and deployment potential of AI-driven ECG interpretation systems.

References

[1] Li, X., Zhou, J., Wang, M., Yang, C., & Sun, G. (2023). Cardiovascular disease and depression: A narrative review. *Frontiers in cardiovascular medicine*, *10*, 1274595.

[2] Jafari, M., Shoeibi, A., Khodatars, M., Ghassemi, N., Moridian, P., Alizadehsani, R., ... & Acharya, U. R. (2023). Automated diagnosis of cardiovascular diseases from cardiac magnetic resonance imaging using deep learning models: A review. *Computers in Biology and Medicine*, *160*, 106998.

[3] Baghdadi, N. A., Farghaly Abdelaliem, S. M., Malki, A., Gad, I., Ewis, A., & Atlam, E. (2023). Advanced machine learning techniques for cardiovascular disease early detection and diagnosis. *Journal of Big Data*, *10*(1), 144.

[4] Mathur, P., Srivastava, S., Xu, X., & Mehta, J. L. (2020). Artificial intelligence, machine learning, and cardiovascular disease. *Clinical Medicine Insights: Cardiology*, *14*, 1179546820927404.

[5] Abubaker, M. B., & Babayiğit, B. (2022). Detection of cardiovascular diseases in ECG images using machine learning and deep learning methods. *IEEE transactions on artificial intelligence*, *4*(2), 373-382.

[6] Pasha, S. N., Ramesh, D., Mohmmad, S., & Harshavardhan, A. (2020, December). Cardiovascular disease prediction using deep learning techniques. In *IOP conference series: materials science and engineering* (Vol. 981, No. 2, p. 022006). IOP Publishing.

[7] Sadr, H., Salari, A., Ashoobi, M. T., & Nazari, M. (2024). Cardiovascular disease diagnosis: a holistic approach using the integration of machine learning and deep learning models. *European Journal of Medical Research*, *29*(1), 455.

[8] Shuvo, S. B., Ali, S. N., Swapnil, S. I., Al-Rakhami, M. S., & Gumaei, A. (2021). CardioXNet: A novel lightweight deep learning framework for cardiovascular disease classification using heart sound recordings. *ieee access*, *9*, 36955-36967.

[9] Chao, H., Shan, H., Homayounieh, F., Singh, R., Khera, R. D., Guo, H., ... & Yan, P. (2021). Deep learning predicts cardiovascular disease risks from lung cancer screening low dose computed tomography. *Nature communications*, *12*(1), 2963.

[10] Mahmud, T., Barua, A., Islam, D., Hossain, M. S., Chakma, R., Barua, K., ... & Andersson, K. (2023, September). Ensemble deep learning approach for ecg-based cardiac disease detection: Signal and image analysis. In *2023 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD)* (pp. 70-74). IEEE.

[11] Liu, X., Wang, H., Li, Z., & Qin, L. (2021). Deep learning in ECG diagnosis: A review. *Knowledge-Based Systems*, *227*, 107187.