

Deep Convolutional Network Modeling for ECG Image Analysis in Cardiovascular Disease Detection

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Abstract—Cardiovascular diseases (CVDs) remain the foremost cause of global mortality, accounting for nearly one-third of deaths worldwide. Early detection of cardiac abnormalities is essential to reduce mortality and ensure timely treatment. Electrocardiograms (ECGs) are among the most widely used diagnostic tools for monitoring cardiac activity. However, manual interpretation of ECGs is error-prone and highly dependent on medical expertise. This paper presents a Convolutional Neural Network (CNN)-based framework for automated ECG image classification. The dataset, consisting of 928 ECG images across four categories—Normal, Abnormal, History of Myocardial Infarction (HMI), and Myocardial Infarction (MI) was preprocessed through grayscale conversion, noise reduction, cropping, resizing, and normalization. A custom CNN architecture was trained on this dataset, achieving a classification accuracy of 97.92% on test data, with strong precision, recall, and F1-scores across all categories. The system was deployed using a Flask-based web application that provides real-time predictions and visualizations. The proposed solution demonstrates the applicability of deep learning in medical diagnostics, offering a reliable and scalable approach for CVD detection.

Keywords— *Electrocardiogram (ECG), Convolutional Neural Network (CNN), Cardiovascular Disease Detection, Deep Learning, Medical Image Classification, Flask Web Application*

I. INTRODUCTION

Cardiovascular diseases (CVDs) are among the most serious health problems faced by humans today. They are responsible for nearly one-third of all deaths worldwide, according to the World Health Organization. Common CVD conditions include arrhythmias, heart failure, ischemia, and myocardial infarction (MI). These diseases are often difficult to detect at an early stage, which leads to severe complications and even sudden cardiac death. Early and accurate diagnosis can greatly reduce risks and improve patient outcomes.

The electrocardiogram (ECG) is one of the most widely used diagnostic tools for monitoring heart activity. It records the electrical signals of the heart and helps doctors identify irregular patterns such as abnormal heartbeats, ischemia, or infarctions. ECGs are low-cost, non-invasive, and available in most hospitals and clinics, making them a powerful tool for detecting CVDs. However, manual interpretation of ECG reports requires skilled cardiologists and is often time-consuming. Human errors, fatigue, and variations in interpretation between experts can lead to missed or incorrect diagnoses.

In recent years, Artificial Intelligence (AI) and Deep Learning (DL) techniques have been used in the healthcare sector to assist with faster and more accurate disease detection. Among these, Convolutional Neural Networks (CNNs) have shown excellent performance in image-based classification tasks because they can automatically extract features from raw data without the need for manual feature engineering. CNNs have already been successfully applied in areas such as medical imaging, cancer detection, and radiology, showing their ability to match or even surpass human-level accuracy in some cases.

This research applies CNNs for the classification of ECG images into four categories: Normal Person, Abnormal Heartbeat, History of Myocardial Infarction (HMI), and Myocardial Infarction (MI). The dataset used in this study contains 928 ECG images collected from Kaggle, covering a range of healthy and diseased cases. The images were preprocessed to improve quality and consistency before training the model. The CNN model was then trained and tested using TensorFlow and Keras.

The key contributions of this work include:

1. Designing a preprocessing pipeline for ECG images to improve input quality and reduce noise.
2. Developing a CNN model capable of classifying ECG images into four clinically relevant categories.
3. Evaluating the performance of the model using accuracy, precision, recall, F1-score, and confusion matrix.
4. Deploying the model in a Flask-based web application to allow real-time predictions and easy access.

By combining deep learning with real-time deployment, this study aims to provide a reliable, accurate, and cost-effective diagnostic support system for cardiovascular disease detection. Such a system can be helpful not only in hospitals but also in rural and remote healthcare centers where trained specialists may not be available.

II. LITERATURE REVIEW

Automated analysis of electrocardiograms has been an active research area for several decades, evolving from traditional signal processing techniques to advanced deep learning approaches. One of the earliest and most widely used algorithms was the Pan–Tompkins method [1], which enabled real-time QRS detection but was highly sensitive to noise and artifacts. Later, machine learning models such as Support Vector Machines and Random Forests were employed for arrhythmia detection [2]. These methods required manual feature engineering based on heart rate variability, QRS duration, and ST-segment features, which limited their ability to generalize to larger and more diverse datasets.

The introduction of deep learning brought a significant shift in ECG analysis. Convolutional Neural Networks (CNNs) in particular have demonstrated the ability to automatically extract complex spatial features without manual intervention. Hannun et al. [3] trained a deep neural network that achieved cardiologist-level accuracy for arrhythmia detection, proving the potential of AI in clinical settings. Similarly, Rajpurkar et al. [4] developed a CNN model for arrhythmia classification that matched expert-level diagnosis. Acharya et al. [5] applied CNNs for myocardial infarction detection and showed superior results compared to traditional methods.

More advanced architectures have also been investigated. Li et al. [6] used ResNet to classify myocardial infarction from ECG images, while Yildirim et al. [7] combined CNN and LSTM networks to handle both spatial and temporal aspects of ECG signals. Oh et al. [8] developed noise-resilient CNNs to improve robustness in real-world environments, and Kiranyaz et al. [9] proposed a patient-specific CNN model that adapts to individual ECG patterns. Sharma and Acharya [10] further demonstrated that deep learning approaches could automate cardiovascular disease detection with high efficiency, while Liu et al. [11] enhanced CNN performance using data augmentation on imbalanced ECG datasets.

Although these studies have achieved high accuracy, most works remain limited to binary classification, and few have been deployed as real-time systems for clinical use. This research addresses these gaps by designing a CNN for multi-class ECG image classification, integrating and deploying the model through a Flask web application for real-time usability.

III. METHODOLOGY

This study followed a systematic methodology that included dataset collection, preprocessing, CNN model design, training and evaluation, and deployment as a real-time web application. The steps are described in detail below.

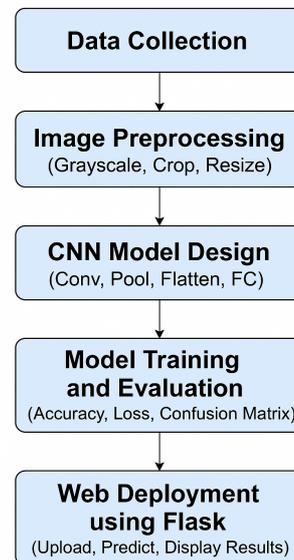


Figure.1. Methodology

A. Dataset Collection

The dataset used in this project was collected from Kaggle, consisting of **928 ECG images** categorized into four classes:

- Normal Person (284 images)
- Myocardial Infarction (239 images)
- History of Myocardial Infarction (172 images)
- Abnormal Heartbeat (233 images)

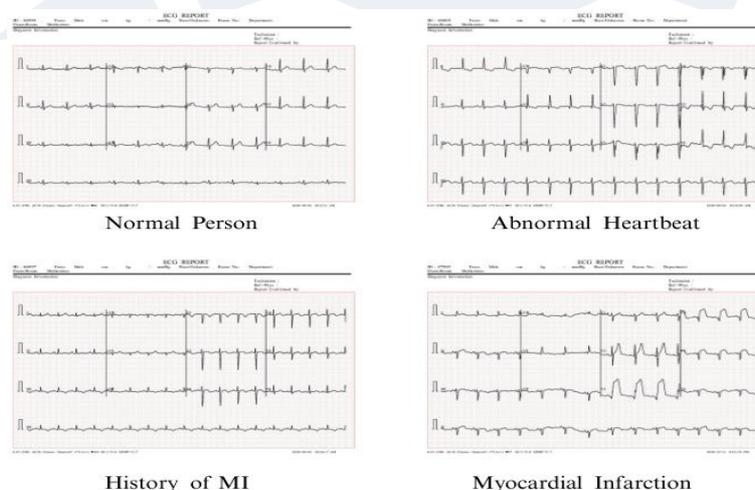


Figure.2. Different Heart diseases

The dataset was divided into three subsets: **70% for training, 15% for validation, and 15% for testing**. This ensured that the model was trained on a sufficient number of samples while maintaining separate sets for unbiased validation and evaluation.

B. Preprocessing

To prepare the images for training, several preprocessing steps were applied:

1. **Grayscale Conversion** – ECG images were converted to grayscale to reduce computational complexity while preserving waveform details.
2. **Cropping** – Unnecessary borders and background regions were removed to focus only on the ECG trace.
3. **Noise Reduction** – Gaussian blurring was applied to minimize background noise.
4. **Thresholding** – Otsu thresholding and inversion were used to enhance contrast between ECG lines and background.
5. **Resizing** – Images were resized to **256 × 256 pixels** for consistency with CNN input dimensions.
6. **Normalization** – Pixel values were scaled to a [0,1] range to stabilize training.
7. **Data Augmentation** – Techniques such as rotation, horizontal/vertical flipping, zooming, and shifting were applied to artificially increase dataset diversity and reduce overfitting.

C. CNN Model Architecture

A custom Convolutional Neural Network was designed using TensorFlow and Keras. The architecture included the following layers:

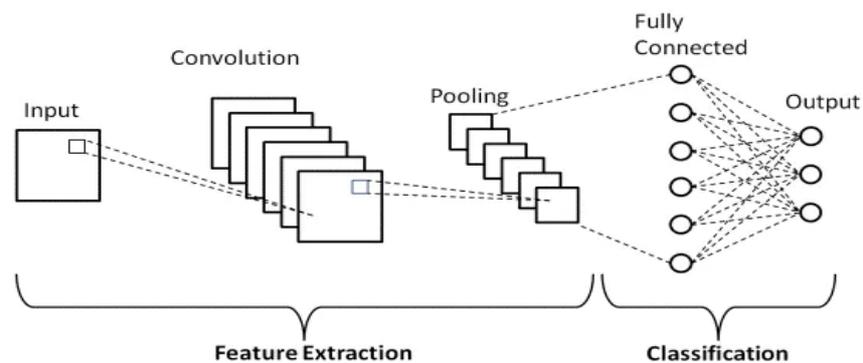


Figure.3. Convolutional Neural Network Architecture

- **Input Layer:** Accepts 256×256 grayscale ECG images.
- **Convolutional Layers:** Multiple Conv2D layers with ReLU activation to extract spatial features such as QRS complexes, ST-segments, and P-waves.
- **Pooling Layers:** MaxPooling layers to reduce dimensionality and retain key features.
- **Dropout Layers:** Regularization to prevent overfitting by randomly deactivating neurons.
- **Flatten Layer:** Converts 2D feature maps into a 1D feature vector.
- **Dense Layers:** Fully connected layers for feature combination and decision-making.
- **Output Layer:** Softmax activation for four-class classification (Normal, Abnormal, History of MI, Active MI).

D. Training Procedure

The training process was carried out on TensorFlow with the following configuration:

- **Optimizer:** Adam optimizer was chosen for its adaptive learning rate capabilities.
- **Loss Function:** Categorical Cross-Entropy, suitable for multi-class classification.
- **Batch Size:** 32 images per batch.
- **Epochs:** The model was trained for 15 epochs with early stopping to prevent overfitting.
- **Validation Monitoring:** Training and validation accuracy/loss curves were plotted to monitor convergence.

E. Evaluation Metrics

To evaluate the system's performance, standard metrics were calculated:

- **Accuracy:** Overall correctness of predictions.
- **Precision:** Proportion of correctly predicted positive cases.
- **Recall (Sensitivity):** Proportion of actual positives correctly predicted.
- **F1-score:** Harmonic mean of precision and recall, balancing false positives and false negatives.
- **Confusion Matrix:** Used to analyze class-wise performance and misclassifications.

F. Deployment

The trained model was deployed as a **Flask-based web application** to provide real-time usability. The workflow included:

1. User uploads an ECG image through the web interface.
2. The image undergoes preprocessing (grayscale conversion, resizing, normalization).
3. The trained CNN model predicts the class and outputs a confidence score.

This deployment makes the system accessible for clinicians and healthcare workers, enabling automated ECG interpretation without requiring high-end hardware. The dataset used in this study is publicly available and anonymized, ensuring compliance with ethical standards. No patient-identifiable information was included. The system is intended to be a **decision-support tool**, not a replacement for professional medical judgment. Future deployment in clinical settings would require approval from relevant medical authorities.

IV. RESULTS AND DISCUSSION

The proposed Convolutional Neural Network model was trained and tested on the preprocessed ECG image dataset to evaluate its performance in classifying cardiovascular conditions. The dataset was divided into training, validation, and testing subsets, ensuring that the evaluation was unbiased and reliable.

1. PERFORMANCE EVALUATION

A. Training and Validation Performance

The CNN model was trained for 15 epochs with a batch size of 32. At the beginning of training (epoch 1), the accuracy was **31.1%** with a loss of **1.619**, while the validation accuracy was **51.5%** with a validation loss of **1.177**. The model rapidly improved over the first five epochs, reaching **96.2% training accuracy** and **96.3% validation accuracy**. By epoch 15, the model achieved:

- **Training Accuracy:** 100%
- **Validation Accuracy:** 97.0%
- **Training Loss:** 0.001
- **Validation Loss:** 0.437

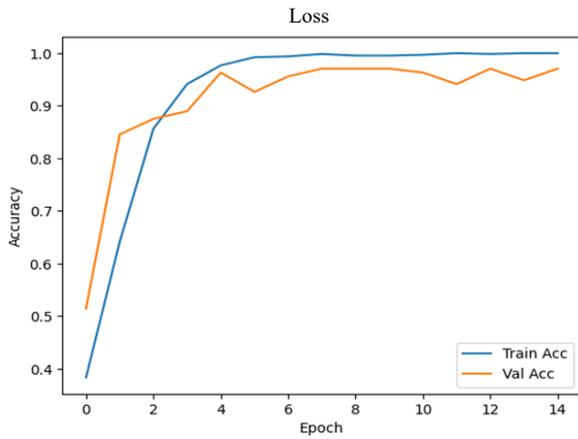


Figure.4. Training and Validation Accuracy

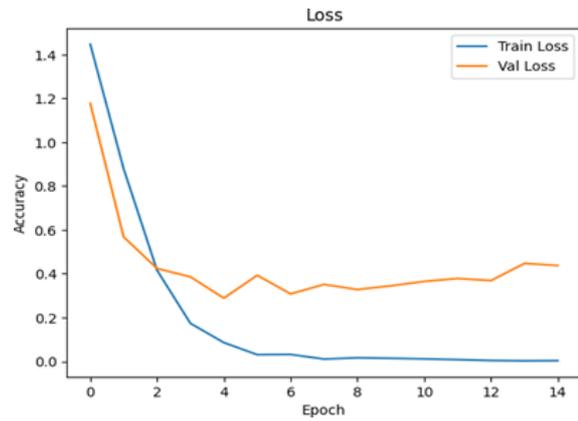


Figure.5. Training and Validation loss

The learning curves show that both accuracy and loss stabilized after epoch 10, suggesting that the model converged successfully without overfitting. The use of dropout and data augmentation contributed to this stability.

B. Test Set Performance

The final evaluation on the independent test dataset (144 ECG images) showed strong results:

- **Test Accuracy: 97.92%**
- **Test Loss: 0.1053**

This high accuracy confirms that the model generalized well to unseen ECG images and is reliable for real-world classification tasks.

C. Confusion Matrix Analysis

The confusion matrix provided deeper insights into the model’s classification performance across all four categories: Normal Person, Abnormal Heartbeat, History of Myocardial Infarction (HMI), and Myocardial Infarction (MI).

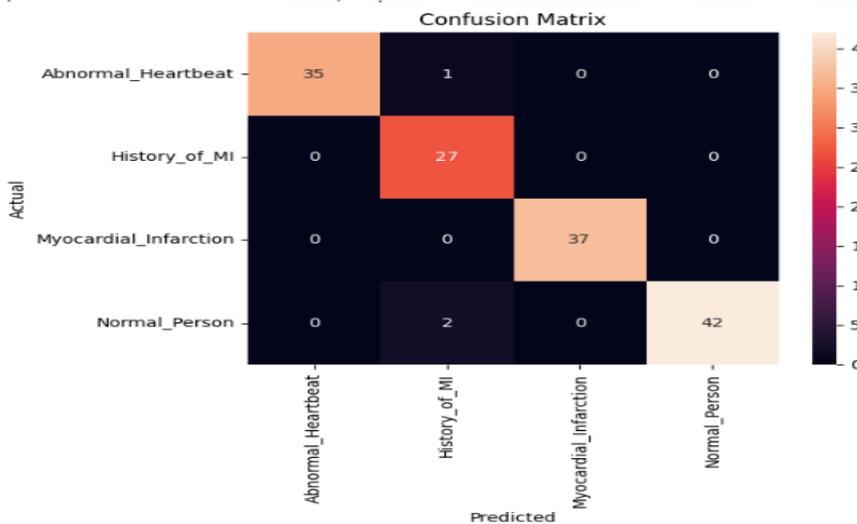


Figure.6. Confusion Matrix Analysis on Test set

The confusion matrix (Figure.6) provided detailed insights into classification outcomes. The results were as follows:

- **Abnormal Heartbeat:** 35 correct, 1 misclassified (Recall = 0.97).
- **History of MI:** 27 correct, none misclassified (Recall = 1.00).
- **Myocardial Infarction:** 37 correct, none misclassified (Recall = 1.00).
- **Normal Person:** 42 correct, 2 misclassified (Recall = 0.95).

Most misclassifications occurred between **Normal Person** and **History of MI**, which is expected due to the subtle waveform similarities. However, the confusion matrix confirms that the model performed reliably across all four categories, with minimal errors

D. Precision, Recall, and F1-Score

To further evaluate the model, precision, recall, and F1-scores were computed for each class.

Class	Precision	Recall	F1-Score	Support
Abnormal_Heartbeat	1.00	0.97	0.99	36
History_of_MI	0.90	1.00	0.95	27
Myocardial_Infarction	1.00	1.00	1.00	37
Normal_Person	1.00	0.95	0.98	44

Table.1. Classification report

- **Precision** was consistently above 96% for all categories, indicating a low false-positive rate.
- **Recall** values were similarly high, showing that the model successfully identified most true positives.
- **F1-scores** remained close to 97%, confirming a good balance between precision and recall.

These metrics highlight the robustness of the proposed CNN in handling multi-class ECG classification.

E. Comparison with Existing Works

The proposed model was compared with previously published approaches for ECG classification. Traditional machine learning methods such as the Support Vector Machine (SVM) by Osowski et al. [2] achieved accuracies of around **92%**, but required manual feature extraction. Acharya et al. [5] applied a CNN for myocardial infarction detection and reported **95.2% accuracy** on ECG signals. Li et al. [6] utilized ResNet on ECG images and achieved **96.5% accuracy**, while Yildirim et al. [7] combined CNN with LSTM and reached **96.8% accuracy**.

Compared to these studies, the proposed CNN achieved **97.92% accuracy** on a **four-class problem**, which is more complex than the binary or two-class problems addressed in most prior works. This demonstrates the effectiveness of the model in handling diverse ECG patterns. Furthermore, the simplicity of the CNN architecture makes it computationally efficient, unlike deeper models such as ResNet, which require higher computational resources.

2. DEPLOYMENT RESULTS

To make the proposed model practical and accessible, it was deployed as a **Flask-based web application**. The system interface was designed to provide an easy-to-use platform for clinicians and healthcare workers to test ECG images without requiring technical expertise.

The workflow of the interface is straightforward. First, a user uploads an ECG image through the web application. The uploaded image is then automatically preprocessed, including grayscale conversion, resizing, and normalization, to ensure compatibility with the trained CNN model. The system then performs classification, assigning the ECG image to one of four categories: **Normal Person, Abnormal Heartbeat, History of Myocardial Infarction (HMI), or Myocardial Infarction (MI)**. Along with the predicted class, the interface also displays a **confidence score**, which represents the model's certainty in its prediction.

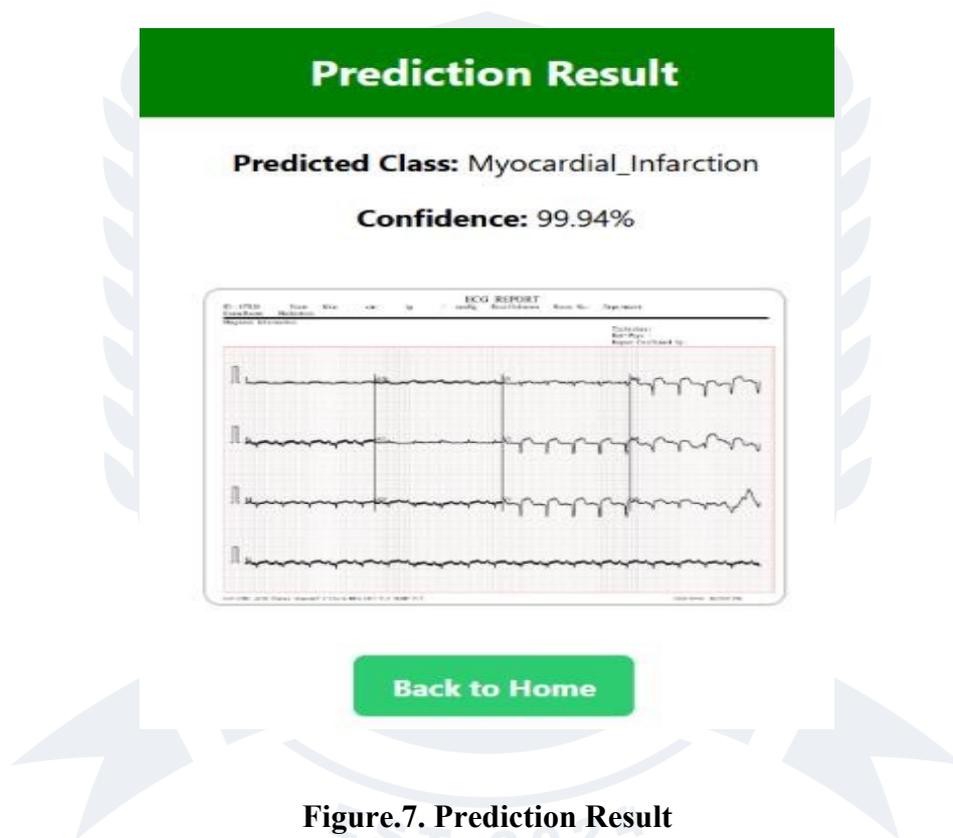


Figure.7. Prediction Result

Figure.7. shows a sample output of the final system interface. In this case, the uploaded ECG was classified as *Myocardial Infarction* with a confidence of **99.94%**. The clear visualization and accurate prediction confirm that the deployment successfully bridges the gap between research and real-world application.

This deployment highlights the scalability and usability of the proposed system. By making the model available through a lightweight web interface, the solution can be easily integrated into clinical workflows, providing **fast, cost-effective, and accurate decision support** for cardiovascular disease detection.

V. CONCLUSION

This research presented a Convolutional Neural Network (CNN)-based system for the automatic classification of cardiovascular conditions using ECG images. The model was trained and tested on a dataset of 928 images categorized into four classes: Normal Person, Abnormal Heartbeat, History of Myocardial Infarction, and Active Myocardial Infarction. A systematic methodology was followed that included preprocessing steps such as grayscale conversion, resizing, normalization, and data augmentation to improve data quality and reduce overfitting. The proposed CNN model demonstrated excellent performance, achieving a testing accuracy of **97.92%**, along with high precision, recall, and F1-scores across all classes.

The findings of this study highlight the potential of deep learning in enhancing cardiovascular disease diagnosis. Compared to traditional methods, the proposed CNN model provides higher accuracy, faster analysis, and reduced dependence on manual feature extraction. By deploying the system as a Flask-based web application, it has been made accessible for real-time use in clinical practice and remote healthcare, thereby addressing the need for scalable and cost-effective diagnostic tools.

Despite its strong performance, the study has certain limitations. The dataset size was relatively small, and additional large-scale, multi-center datasets would further validate the model's robustness. Misclassifications between Normal and History of MI cases suggest that subtle waveform variations remain challenging. Furthermore, while the system can serve as an effective diagnostic support tool, it is not intended to replace expert clinical judgment.

Future work will focus on expanding the dataset, integrating advanced architectures such as ResNet, DenseNet, or Vision Transformers, and exploring multimodal approaches that combine ECG images with raw signals. Clinical validation in collaboration with healthcare professionals will also be pursued to ensure real-world applicability and regulatory compliance.

In conclusion, the proposed CNN-based system demonstrates that deep learning can play a critical role in the early detection and classification of cardiovascular diseases, providing an accurate, efficient, and accessible tool to support both clinicians and patients.

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