

An Automated ECG Image-Based Framework for Cardiovascular Disease Classification Using Transfer Learning

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Abstract: Cardiovascular diseases (CVDs) are among the leading causes of mortality worldwide, making early and accurate diagnosis essential for effective treatment and patient care. Electrocardiogram (ECG) images provide valuable information about the electrical activity of the heart and play a significant role in identifying various cardiac abnormalities. However, manual interpretation of ECG images is time-consuming and requires expert medical knowledge. This paper presents a deep learning-based approach for automated cardiovascular disease detection using ECG images.

The proposed system utilizes a Convolutional Neural Network (CNN) with the pre-trained VGG16 architecture for feature extraction and image classification. ECG images are pre-processed through resizing, normalization, and data preparation before being passed to the CNN-VGG16 model. The model classifies ECG images into four categories: Myocardial Infarction, History of Myocardial Infarction, Abnormal Heartbeat, and Normal ECG. A Streamlit-based web application is developed to provide an interactive interface where users can upload ECG images and obtain real-time predictions along with confidence scores, prediction probabilities, disease information, and medical recommendations.

The proposed system aims to support healthcare professionals by providing a fast, reliable, and user-friendly tool for automated ECG image analysis. Experimental results demonstrate that the CNN-VGG16 model effectively extracts meaningful features from ECG images and achieves accurate classification, making it a promising approach for computer-aided cardiovascular disease diagnosis.

Keywords:

Cardiovascular Disease, Electrocardiogram (ECG), Deep Learning, Convolutional Neural Network (CNN), VGG16, Image Classification, Streamlit, Medical Image Analysis.

INTRODUCTION

Heart disease is one of the leading causes of death worldwide and remains a major public health concern. Early and accurate diagnosis is essential for reducing mortality and improving patient outcomes. Several researchers have investigated artificial intelligence and deep learning techniques for cardiovascular disease detection using ECG signals and images. Abubaker and Babayiğit explored machine learning and deep learning methods for detecting cardiovascular diseases from ECG images [1]. Mhamdi et al. proposed an artificial intelligence-based approach for cardiac disease diagnosis using ECG images on embedded systems [2]. Dhandapani et al. developed a hybrid deep learning framework for heart disease prediction using ECG signal images [3]. Aversano et al. investigated CNN-based techniques for the early diagnosis of cardiac diseases using ECG images [4].

Other studies have also demonstrated the application of deep learning and machine learning techniques for cardiovascular disease prediction. Baboo et al. proposed a deep learning approach using ECG data [5], while Rautela et al. investigated cardiovascular disorder identification through ECG image analysis [6]. Aarthy and Mazher Iqbal explored deep learning for early cardiovascular disease detection from ECG signals [7]. Bhargale et al. investigated machine learning-based heart disease prediction using ECG images [8].

These studies demonstrate the growing potential of artificial intelligence for automated cardiovascular disease detection. However, there is still a need for effective image-based multiclass classification approaches that can accurately distinguish different ECG conditions. Therefore, this study proposes a VGG16-based deep learning framework for classifying ECG images into four categories: MI, HMI, AHB, and Normal ECG. Motivated by these studies, this research proposes a VGG16-based Convolutional Neural Network (CNN) for heart disease prediction using ECG images. The ECG images are pre-processed, resized to 224×224 pixels, and classified into four categories: Myocardial Infarction (MI), History of Myocardial Infarction (HMI), Abnormal Heartbeat (AHB), and Normal ECG. The trained model is deployed as a Streamlit-based web application to provide real-time ECG image classification with prediction results and confidence scores.

The main contributions of this study are summarized as follows:

- Development of a CNN-VGG16 based system for automated classification of ECG images into four cardiovascular categories.
- Application of image preprocessing and normalization techniques to prepare ECG images for deep learning classification.
- Utilization of transfer learning through the VGG16 architecture for extracting meaningful features from ECG images.
- Development of a user-friendly Streamlit web application for real-time ECG image prediction.
- Presentation of prediction confidence, probability distribution, and prediction time to improve the usability of the proposed system.

RELATED WORK

Several machine learning and deep learning techniques have been investigated for automated cardiovascular disease detection using ECG signals and ECG images. Abubaker and Babayigit [1] investigated machine-learning and deep-learning methods for detecting cardiovascular diseases from ECG images. Their study demonstrated the potential of ECG image representations for automated cardiovascular disease classification. Mhamdi et al. [2] proposed an artificial-intelligence-based approach for cardiac disease diagnosis and prediction using ECG images. The study also investigated implementation on embedded systems, highlighting the possibility of deploying AI-based ECG analysis on resource-constrained devices. Dhandapani et al. [3] developed a hybrid deep-learning framework for heart disease prediction using ECG signal images. Their work demonstrated that deep-learning techniques can extract useful patterns from ECG image representations for automated cardiovascular disease prediction. Rautela et al. [6] investigated the identification of cardiovascular disorders through ECG image analysis. Their study highlights the usefulness of ECG images as an input representation for automated cardiovascular disorder detection. Aversano et al. [4] investigated CNN-2D techniques for the early diagnosis of cardiac diseases using ECG images. Their study showed the applicability of convolutional neural networks for extracting discriminative features directly from ECG image data. Baboo et al. [5] proposed a deep-learning approach for cardiovascular disease prediction using ECG data. Their work explored the use of automatically learned ECG features to support cardiovascular disease prediction. Aarthy and Mazher Iqbal [7] proposed a deep-learning approach for the early detection of cardiovascular diseases from ECG signals. Their work demonstrates the potential of deep-learning models to automatically identify relevant patterns from ECG signals.

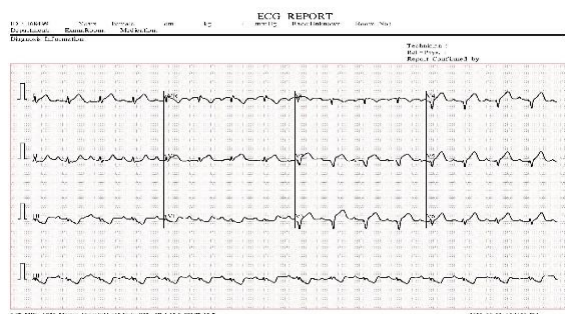
DATASET DESCRIPTION

The dataset used in this study consists of 42,073 ECG images collected for cardiovascular disease classification. The dataset contains ECG recordings representing four clinically relevant categories: Myocardial Infarction (MI), History of Myocardial Infarction (HMI), Abnormal Heartbeat (AHB), and Normal ECG. These categories enable the proposed deep learning model to distinguish between normal cardiac activity and different abnormal cardiovascular conditions. Table 1 summarizes the distribution of images and the description of each categories.

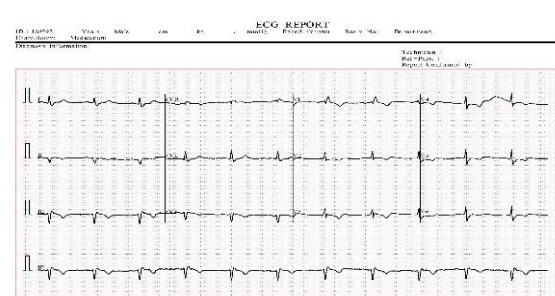
Table 1. Description of ECG Categories Used for Heart Disease Classification

Class	Number of Images	Description
Myocardial Infarction (MI)	11,061	ECG images from patients with myocardial infarction.
History of Myocardial Infarction (HMI)	7,693	ECG images from patients with a previous history of myocardial infarction.
Abnormal Heartbeat (AHB)	10,490	ECG images showing abnormal heartbeat or cardiac rhythm patterns.
Normal ECG	12,829	ECG images representing normal cardiac activity.

Representative ECG images from the four heart disease categories—Normal, Myocardial Infarction (MI), History of Myocardial Infarction (HMI), and Abnormal Heartbeat (AHB)—are shown in Figure 1. These sample ECG images highlight the characteristic patterns of each category and were used for training and evaluating the proposed VGG16-based Convolutional Neural Network (CNN) model for heart disease prediction.



a) MI



b) HMI

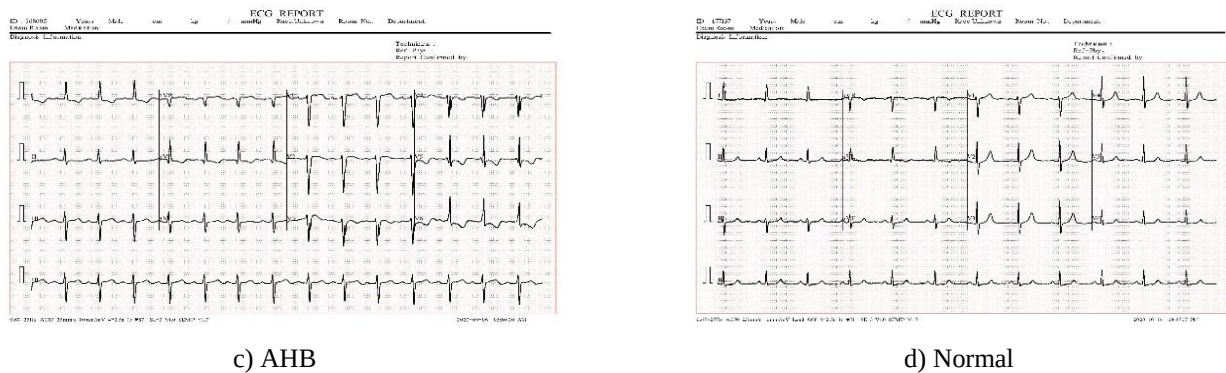


Figure 1. Representative ECG Images from Different Classification Categories

3.1 Dataset Splitting

The ECG image dataset was divided into training and validation subsets for model development and performance evaluation. The training subset was used to train the VGG16-based classification model, while the validation subset was used to monitor model performance during training and fine-tuning. The images were organized into four classes: Myocardial Infarction, History of Myocardial Infarction, Abnormal Heartbeat, and Normal ECG. The same class structure was maintained in both subsets to ensure consistent multi-class classification.

Table 2. Dataset Splitting

Subset	Percentage	Purpose
Training Set	70%	Used to train the VGG16 model and learn relevant features from ECG images.
Validation Set	30%	Used to monitor model performance during training and fine-tuning and to evaluate generalization during model development.

As indicated in Table 2, the dataset was divided into 70% training and 30% validation data. This split enables the VGG16-based model to learn relevant features effectively from the training data while monitoring its performance and generalization ability using the validation data during the training and fine-tuning process.

PURPOSED METHODOLOGY

The proposed system uses a VGG16-based transfer learning and fine-tuning approach for classifying ECG images into four categories: Myocardial Infarction (MI), History of Myocardial Infarction (HMI), Abnormal Heartbeat (AHB), and Normal ECG. The ECG image dataset is pre-processed through image resizing, pixel value normalization, and data augmentation to improve model performance and generalization. The dataset is then divided into training and validation sets for effective learning. A pre-trained VGG16 model is fine-tuned for feature extraction and classification. The trained model is evaluated using performance metrics such as accuracy, precision, recall, F1-score, confusion matrix, and ROC curve. Finally, the trained model is deployed as a Streamlit web application for real-time ECG image classification and heart disease prediction.

4.1 Work Flow

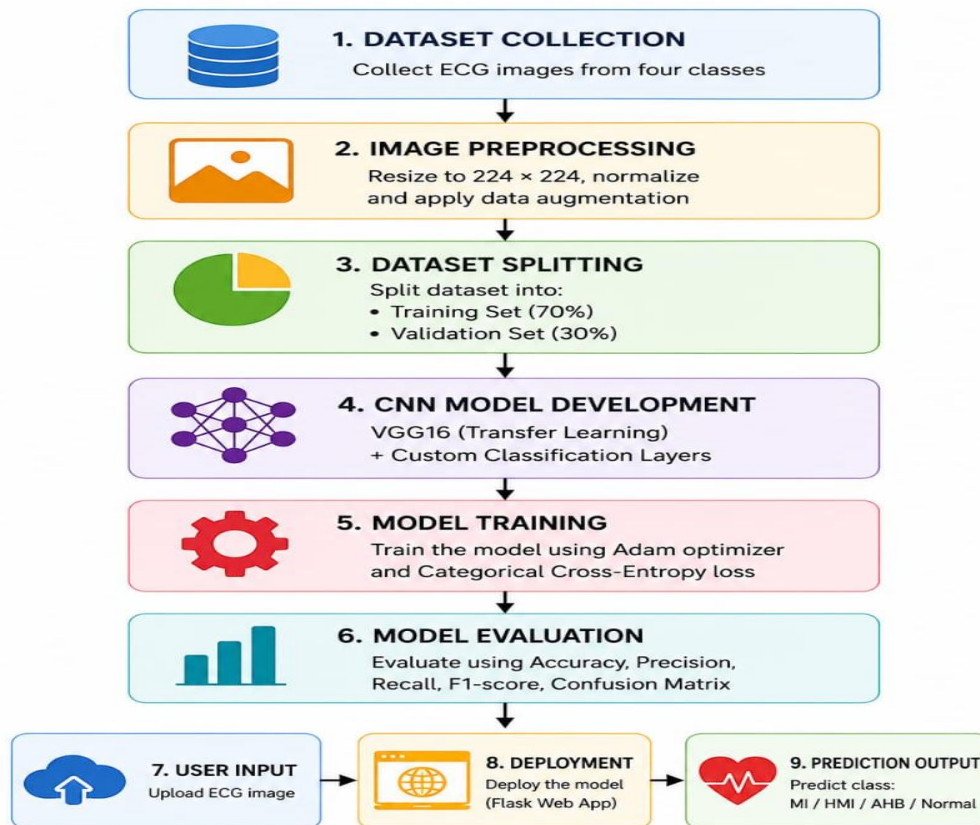


Figure 2: Workflow of Proposed ECG Classification System

Workflow Steps

- Step 1: ECG Dataset Collection – Collect ECG images from four cardiac categories.
 Step 2: Image Preprocessing – Resize, rescale, and augment ECG images.
 Step 3: Dataset Splitting – Divide the dataset into 70% training and 30% validation sets.
 Step 4: VGG16 Model Development – Use pretrained VGG16 with ImageNet weights for transfer learning.
 Step 5: Model Training – Train the VGG16-based model using the training dataset.
 Step 6: Fine-Tuning – Unfreeze and fine-tune the last four VGG16 layers.
 Step 7: Model Evaluation – Evaluate using accuracy, precision, recall, F1-score, and confusion matrix.
 Step 8: Model Deployment – Save the fine-tuned model and integrate it into a Streamlit application.
 Step 9: User Input – Upload an ECG image through the Streamlit application.
 Step 10: Prediction Output – Predict and display the corresponding ECG disease category and confidence.

4.2 CNN Architecture

A Convolutional Neural Network (CNN) is a deep learning architecture widely used for image classification and feature extraction. It automatically learns important features from input images through convolution and pooling operations. The extracted features are then transformed into a one-dimensional representation and passed through fully connected layers for classification. Figure 3 illustrates the general design of a CNN.

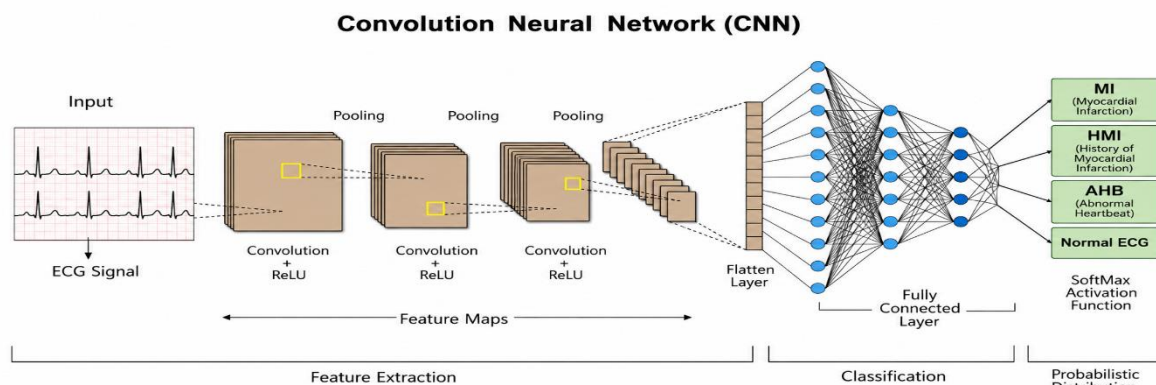


Figure 3: General Architecture of a Convolutional Neural Network (CNN)

The figure represents the general architecture of a Convolutional Neural Network used for image classification. The convolution layer extracts important visual features from the input ECG image, while the ReLU activation introduces non-linearity and the pooling layer reduces the feature dimensions. The Flatten layer converts the extracted feature maps into a one-dimensional vector, which is processed by the fully connected layer. Finally, the Softmax output layer assigns the input image to the appropriate classification category.

For efficient feature extraction and multiclass ECG classification, the suggested CNN design includes several Convolutional, Max-Pooling, Dropout, Flatten, and Dense layers. In order to reduce overfitting and spatial dimensions. Table 3 displays the entire layer-wise architecture of the proposed CNN model displays the entire layer -wise architecture of the proposed CNN model.

Table 3: The Suggested CNN model's layer-wise design
Model: "functional_1"

Layer (type)	Output Shape	Param #
input_layer_1 (Input Layer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1,792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36,928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73,856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147,584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295,168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590,080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590,080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1,180,160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2,359,808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2,359,808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten_1 (Flatten)	(None, 25088)	0
dense_2 (Dense)	(None, 512)	12,845,568
dropout_1 (Dropout)	(None, 512)	0
sssdense_3 (Dense)	(None, 4)	2,052

Total params: 27,562,308 (105.14 MB)

Trainable params: 12,847,620 (49.01 MB)

Non-trainable params: 14,714,688 (56.13 MB)

The performance of the proposed CNN model depends on the appropriate selection of training hyperparameters. The model training parameters used for the classification task are presented in Table 4.

Table 4. Model-Training Parameters

Parameter	Value
Model	VGG16
Input Image Size	224 x 224 x 3
Classes	4
Data Split	70% / 30%
Optimizer	Adam
Batch Size	16
Initial Epochs	20
Initial LR	1×10^{-4}
Fine-Tuning	Last 4 Layers
Fine-Tuning Epochs	10
Fine-Tuning LR	1×10^{-5}
Output	Softmax

The proposed cardiovascular prediction system was developed using various software tools, programming libraries, and frameworks for dataset preprocessing, VGG16 model development, training, evaluation and deployment. The tools used in this study are summarized in Table 5.

Table 5. Tools Used in This Experiment

Component	Specification
Operating System	Windows 11 (64-bit)
Development Environment	Google Colab
Programming Language	Python 3.11.9
IDE / Code Editor	Visual Studio Code, Google Colab
Deep Learning Framework	TensorFlow 2.20
Libraries	NumPy, Pandas, Matplotlib, Scikit-learn, Seaborn
Web Framework	Streamlit
Frontend	HTML, CSS
Dataset	ECG Image Dataset
GPU	NVIDIA Tesla T4 (Google Colab GPU)

4.3 VGG-16 Architecture

VGG16 is a deep convolutional neural network widely used for image feature extraction and classification. In the proposed system, the pre-trained VGG16 network is used as a transfer learning model for extracting important features from ECG images. The input ECG images are resized to $224 \times 224 \times 3$ pixels and passed through five convolutional blocks to learn hierarchical features. Figure 4 illustrates the general design of VGG-16 Model.

VGG16 Architecture

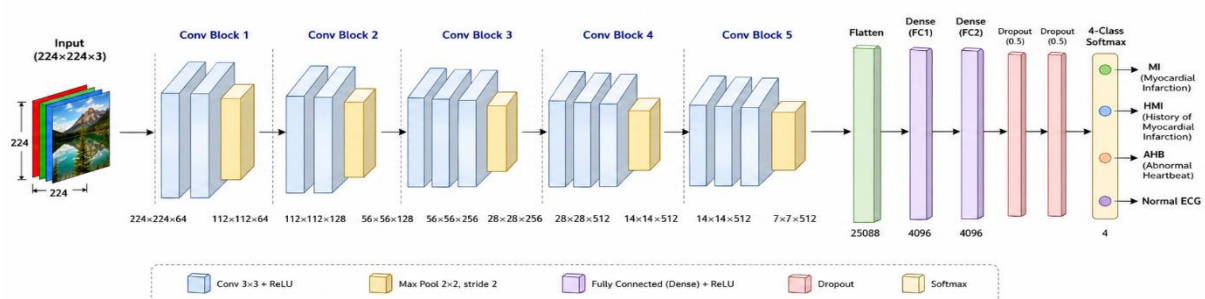


Figure 4. VGG16 Architecture for ECG Image Classification

The figure represents the VGG16 architecture adopted for the proposed ECG classification system. The convolutional blocks extract hierarchical features from the input ECG images, ranging from low-level patterns to more complex visual characteristics. The Flatten and Dense layers transform the extracted features into a suitable representation for classification, while Dropout helps reduce overfitting. Finally, the Softmax output layer produces the probabilities for the four ECG categories: Myocardial Infarction, History of Myocardial Infarction, Abnormal Heartbeat, and Normal ECG.

METRICS EVALUATION

The performance of the proposed VGG16-based ECG classification model was evaluated using four standard classification metrics: Accuracy, Precision, Recall, and F1-Score. These metrics provide a comprehensive assessment of the model's overall classification performance and its ability to correctly identify different ECG categories. The mathematical formulations of the evaluation metrics are given below.

1. Accuracy: Accuracy measures the proportion of correctly classified ECG images among all the evaluated images.

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

2. Precision: Precision measures the proportion of correctly predicted positive samples among all samples predicted as positive.

$$Precision = \frac{TP}{TP + FP}$$

3. Recall: Recall measures the proportion of actual positive samples that are correctly identified by the model.

$$Recall = \frac{TP}{TP + FN}$$

4. F1-Score: F1-Score represents the harmonic mean of Precision and Recall, providing a balanced measure of the model's classification performance.

$$F1-Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

5.1 Performance Results

The proposed VGG16-based ECG classification model was evaluated using four standard performance metrics: accuracy, precision, recall, and F1-score. These metrics provide an overall assessment of the model's ability to correctly classify the four ECG categories. The obtained results indicate strong and balanced classification performance. The overall performance values are presented in Table 6.

Table 6. Performance Results of VGG16- based CNN

Metric	Value%
Accuracy	90.94
Precision	91.22
Recall	90.94
F1-Score	91.02

The table 6 illustrates the performance results demonstrate the effectiveness of the proposed VGG16-based transfer learning model for ECG image classification. The model achieved an accuracy of 90.94%, precision of 91.22%, recall of 90.94%, and F1-score of 91.02% on the validation dataset. These high evaluation metrics indicate that the model can accurately distinguish among the four ECG categories.

5.2 Training and Validation Performance

The training and validation accuracy curves illustrate the learning performance of the proposed VGG16 model during the training process. Training accuracy represents the model's performance on the training dataset, while validation accuracy indicates its generalization performance on unseen validation data. The accuracy curves across the training epochs are shown in Figure 4.

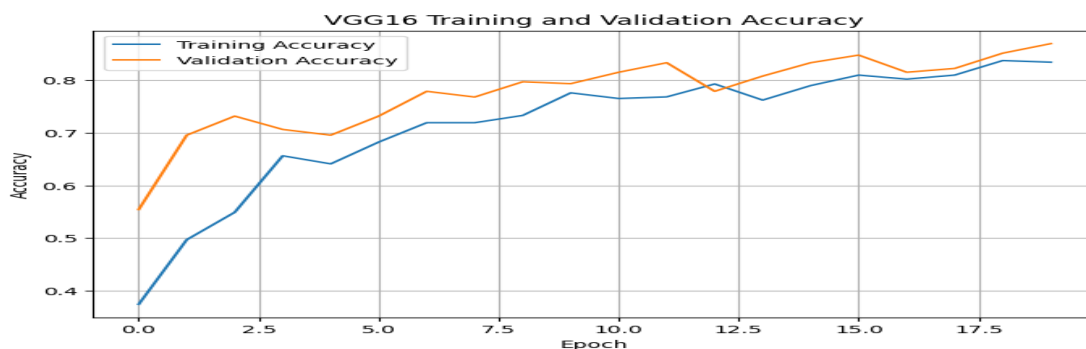


Figure 4. Training and Validation Accuracy of the Proposed VGG16 Model

The figure 4 illustrates the training and validation accuracy achieved during the model training process. Both curves show a steady improvement as the number of training epochs increases, indicating effective learning by the proposed VGG16 model. The validation accuracy closely follows the training accuracy, demonstrating good generalization performance. The final validation accuracy of approximately 90.94% confirms the effectiveness of the proposed approach.

Training and Validation Loss

The training and validation loss curves illustrate the reduction in prediction error of the proposed VGG16 model during training. Training loss represents the error calculated on the training dataset, whereas validation loss indicates the model's performance on unseen validation data. The loss curves across the training epochs are presented in Figure 5.

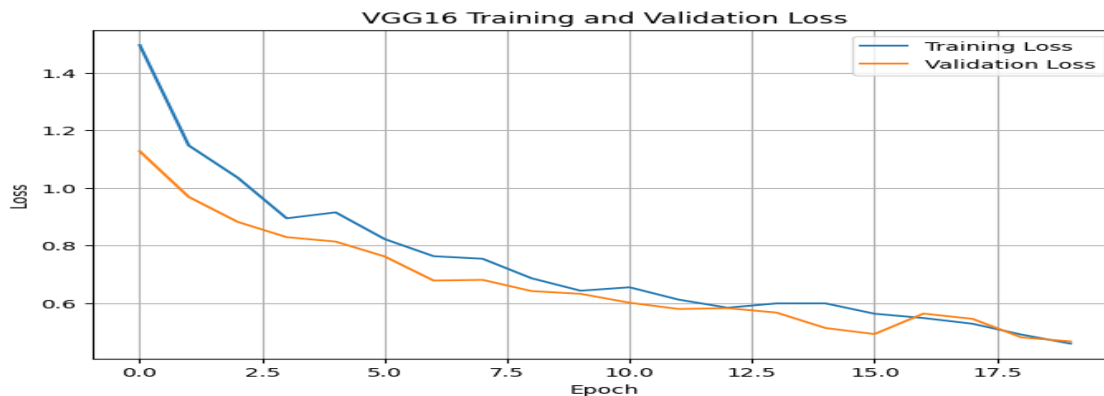


Figure 5. Training and Validation Loss of the Proposed VGG16 Model

The figure 5 presents the training and validation loss observed during model training. Both loss curves decrease consistently with increasing epochs, indicating successful optimization of the model parameters. The small difference between the training and validation loss suggests that overfitting has been effectively controlled. These results demonstrate the stability and convergence of the proposed VGG16-based ECG classification mode

5.3 Classification Report

The classification report summarizes the class-wise performance of the proposed VGG16 model using precision, recall, F1-score, and support. It provides a detailed comparison of the model's performance across the four ECG categories. The classification results obtained from the validation dataset are presented in Table 7.

Table 7. Classification Report of ECG Images

ECG Category	Precision	Recall	F1-Score
Myocardial Infarction	0.97	1.00	0.99
History of MI	0.77	0.84	0.80
Abnormal Heartbeat	0.95	0.90	0.93
Normal ECG	0.91	0.88	0.90

As shown in the Table 7, The classification results show that the proposed VGG16 model achieved strong performance across the four ECG categories. The Myocardial Infarction class obtained the highest F1-score of 0.99, with 97% precision and 100% recall, while the Abnormal Heartbeat class achieved an F1-score of 0.93. The History of Myocardial Infarction class recorded a comparatively lower F1-score of 0.80, whereas the Normal ECG class achieved an F1-score of 0.90. Overall, the model obtained a weighted average of 0.91 for precision, recall, and F1-score across 276 test samples, demonstrating effective multi-class ECG classification.

5.4 Confusion Matrix

To further assess the classification performance, a confusion matrix was generated to compare the actual and predicted ECG classes. The matrix provides a detailed view of the model's classification accuracy and helps identify correctly samples as well as any misclassifications. Figure 6. presents the confusion matrix of developed VGG-16 model.

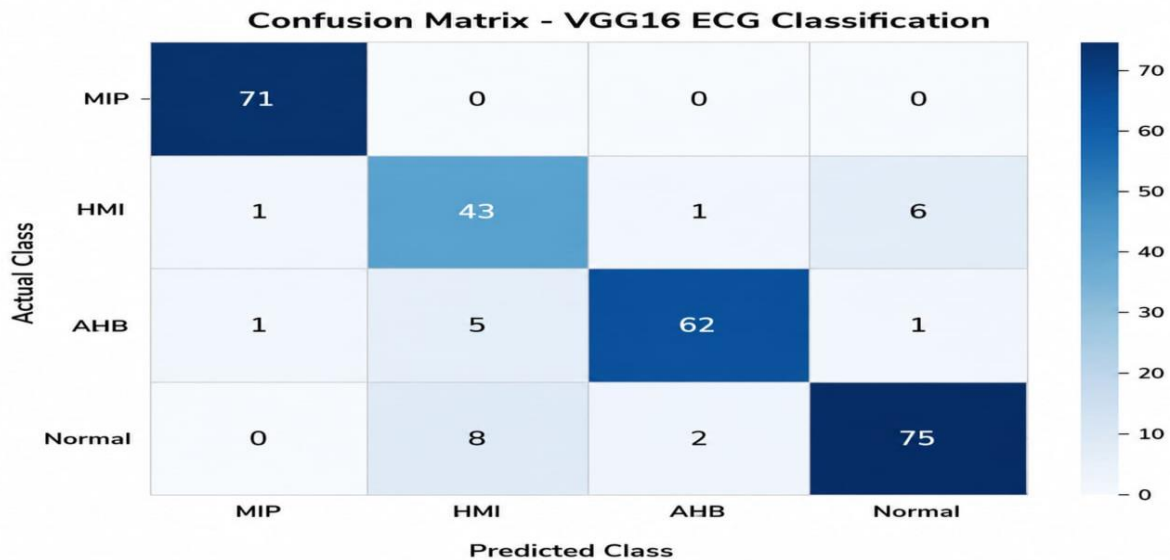


Figure 6. Confusion Matrix of the Proposed VGG16 Model

As shown in the Figure 6, The confusion matrix shows that 71 out of 71 Myocardial Infarction samples were correctly classified, while 43 out of 51 History of Myocardial Infarction samples were correctly identified. For the Abnormal Heartbeat and Normal ECG classes, 62 out of 69 and 75 out of 85 samples were correctly classified, respectively. Overall, 251 out of 276 samples were correctly predicted, resulting in an overall classification accuracy of approximately 90.94%.

SYSTEM DEPLOYMENT

The trained VGG16-based ECG classification model was integrated into a Streamlit web application to provide an interactive platform for automated ECG image classification. The application allows users to upload ECG images and obtain real-time classification results along with the corresponding confidence score. The integration of the VGG16 model with the Streamlit interface provides a simple, fast, and user-friendly platform for automated ECG-based cardiac disease classification. Figure 7 presents the developed Streamlit-based ECG classification application.

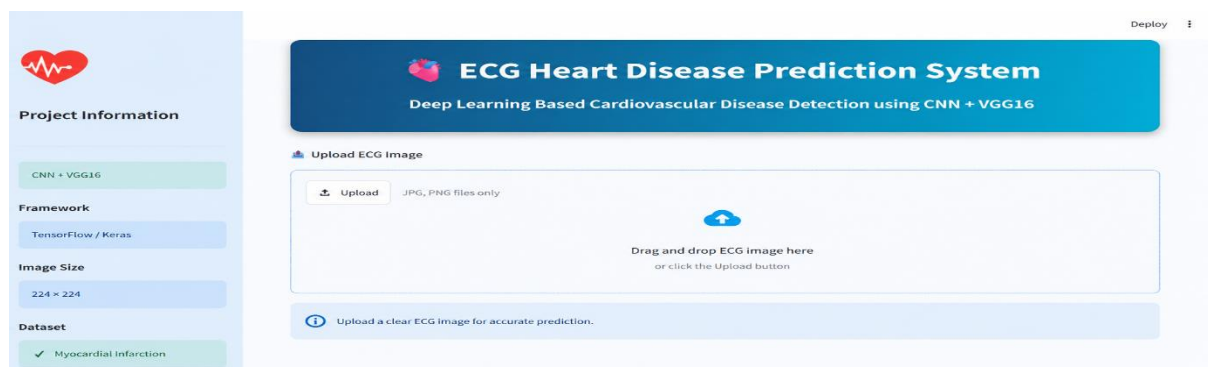


Figure 7. Streamlit - Based Web Application for ECG Heart Disease Classification

As shown in Figure 7, the application consists of a user-friendly interface that allows users to upload ECG images and obtain automated classification results. The system processes the uploaded ECG image using the trained VGG16 model and provides the predicted ECG category along with the corresponding confidence score.

6.1 Image Upload Interface

The developed Streamlit-based web application provides a simple and user-friendly interface for uploading ECG images. Users can select an ECG image from their device and submit it for analysis using the trained VGG16 classification model. Figure 8 illustrates the ECG image upload interface of the proposed ECG classification system.

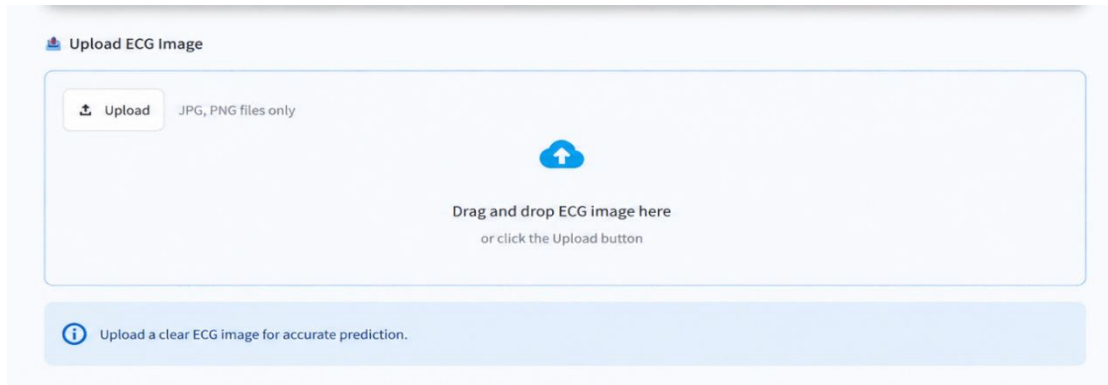
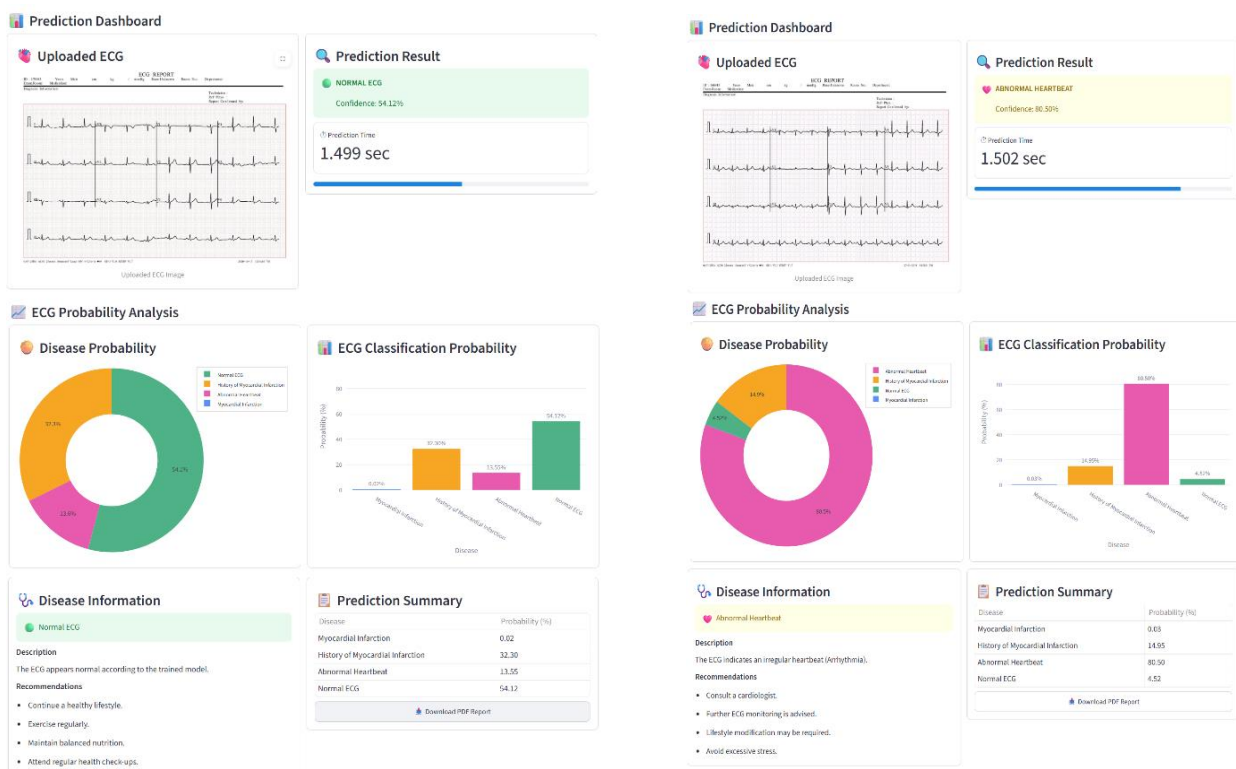


Figure 8. ECG Image Upload Interface of the Streamlit Web Application

The developed Streamlit web application's image upload interface is shown in Figure 8. The Upload ECG Image option allows users to upload an ECG image from their device for analysis. The interface provides a simple and user-friendly layout for selecting and uploading ECG images prior to classification using the proposed VGG16 model.

6.2 Prediction Results

After uploading the ECG image, the trained VGG16 model analyzes the input image and determines the corresponding ECG category. The application displays the predicted class, confidence score, prediction time, and class-wise probability distribution, providing clear and interpretable prediction results. Figure 9 presents the prediction output generated by the proposed VGG16-based ECG classification system.



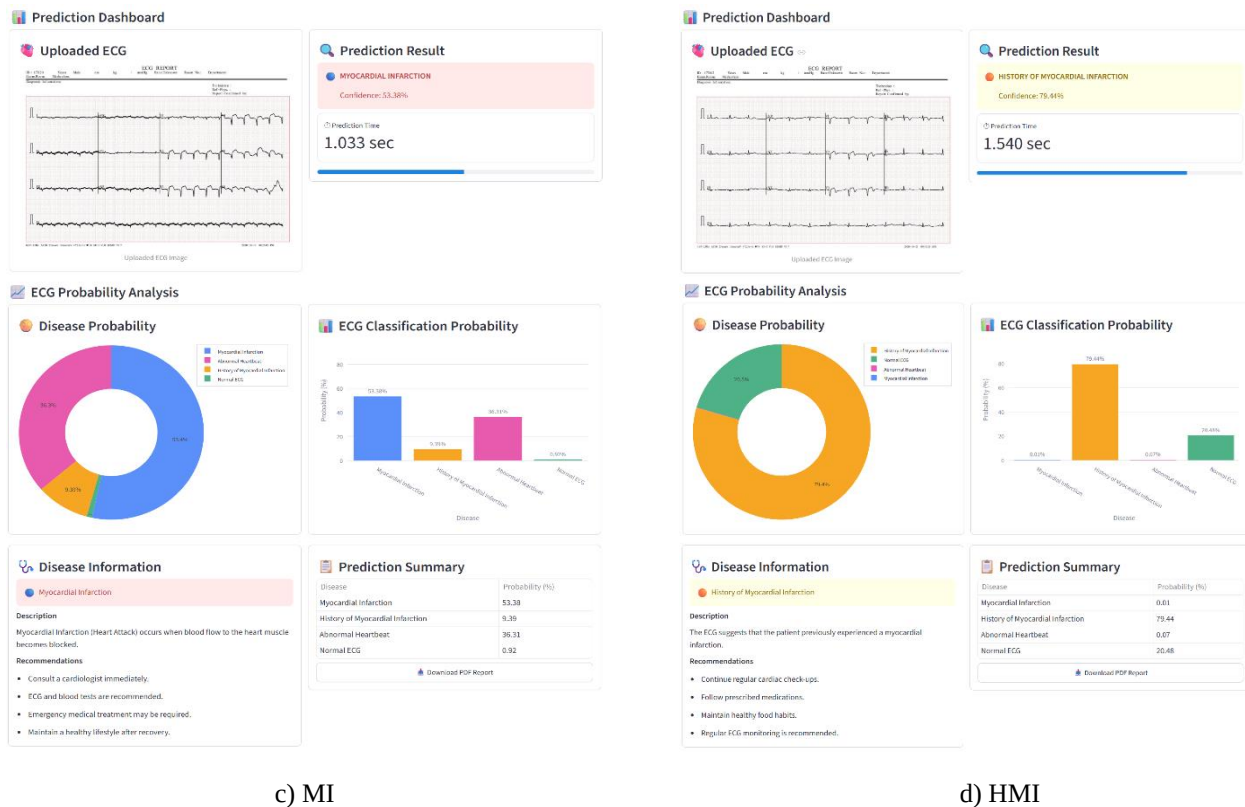


Figure 9. Prediction Output of the Proposed VGG16-Based ECG Classification System

As Shown in Figure 9, The prediction results demonstrate that the developed system can classify uploaded ECG images into the predefined cardiac categories using the fine-tuned VGG16 model. The application displays the predicted category, confidence score, prediction time, and class-wise probability distribution for better interpretation of the output. The results confirm the successful integration of the trained model with the Streamlit-based application. This demonstrates the practical usability of the proposed system for automated ECG image classification.

COMPARISON WITH EXISTING MODELS

This is particularly relevant to your project because it uses the Medley ECG image dataset, which contains the same four categories you are working with: Normal, Myocardial Infarction, History of MI, and Abnormal Heartbeat. The study compares a lightweight DCNN with several traditional classifiers. The reported accuracies include 84.9% for Classification Tree and 80.6% for KNN, table 8. Shows comparison.

Table 8. Comparison of ECG Image Classification Methods

Study	Year	Dataset/Input	Method	Accuracy (%)
MLTP-based CVD detection	2026	ECG images / Mendeley	KNN	80.6
MLTP-based CVD detection	2026	ECG images / Mendeley	Classification Tree	84.9
Proposed study	2026	ECG images	VGG16-based CNN	90.94

CONCLUSION AND UPCOMING PROJECT

This study developed a VGG16-based deep learning framework for automated cardiovascular disease detection and multiclass classification using ECG images. The framework uses preprocessing, normalization, data augmentation, and transfer learning to improve the learning process and classification performance. The model classifies ECG images into four categories: Myocardial Infarction, History of Myocardial Infarction, Abnormal Heartbeat, and Normal ECG. The experimental results showed an overall classification accuracy of approximately 91%, demonstrating the effectiveness of the proposed approach. Precision, recall, F1-score, and confusion matrix were used to evaluate the model performance. The trained model was successfully integrated into a Streamlit web application that allows users to upload ECG images and obtain predictions with confidence scores, probabilities, prediction time, and graphical visualizations. The application also provides a downloadable PDF report containing the prediction results and disease information. Overall, the system shows the potential of deep learning as a computer-aided ECG screening and research tool, although it should not replace professional medical diagnosis.

In future work, the proposed system can be trained and evaluated using larger and more diverse ECG image datasets to improve its robustness and generalization. Different preprocessing, augmentation, and fine-tuning techniques can be explored to reduce

misclassification between similar ECG categories. Grad-CAM and other Explainable AI techniques can be incorporated to identify the important regions influencing model predictions. The application can also be extended to support real-time ECG analysis and integration with portable ECG devices, cloud platforms, and mobile healthcare applications. Model optimization can further reduce computational requirements and improve prediction speed on low-resource devices. Finally, independent dataset testing and validation by qualified healthcare professionals can be conducted to assess the reliability and practical applicability of the proposed system in real-world healthcare environments.

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