Deep Learning-Based Myocardial Infarction Detection from ECG Images

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***Abstract*—Myocardial Infarction (MI) remains a leading cause of global mortality, where timely detection through Electrocardiogram (ECG) analysis is critical for effective intervention. Conventional diagnostic techniques and early machine learning methods often fall short in handling the complex and variable nature of ECG signals, particularly in accurately identifying MI cases. This study presents a deep learning-based ECG classification framework utilizing EfficientNet-B0 enhanced with a Multi-Scale Attention (MSA) mechanism to improve the extraction of both localized and global features from ECG images. The model classifies inputs into four clinically significant categories: Myocardial Infarction, History of MI, Abnormal Heartbeat, and Normal ECG. A lightweight and user-friendly interface enables image upload and real-time diagnosis, supported by integrated explainable AI techniques such as Grad-CAM and Integrated Gradients to enhance clinical interpretability. Evaluation results demonstrate a superior classification accuracy of 96%, outperforming baseline convolutional models and attention-augmented DenseNet architectures. The findings highlight the potential of attention-enhanced deep networks combined with interpretability tools in supporting accurate and transparent cardiac diagnostics.**

***Index Terms*—Electrocardiogram (ECG), Myocardial Infarction (MI), Deep Learning, Multi-Scale Attention, Explainable AI (XAI)**

I. Introduction

Electrocardiograms (ECGs) are among the most widely used tools for diagnosing heart-related conditions, including Myocardial Infarction (MI), arrhythmias, and structural abnormalities. Clinical interpretation of ECG waveforms requires considerable expertise, and even skilled practitioners face challenges in detecting subtle waveform deviations, especially under high workload conditions or in resource-constrained settings. In many underprivileged or rural regions, the scarcity of trained cardiologists further exacerbates diagnostic delays and increases the risk of undetected cardiac conditions.

The integration of artificial intelligence (AI), particularly deep learning, has significantly advanced medical image interpretation. Convolutional Neural Networks (CNNs) have demonstrated substantial performance gains across tasks such as medical imaging classification, segmentation, and anomaly detection. However, many existing AI-based ECG classification systems either lack sufficient interpretability or provide binary predictions that limit their clinical value. Furthermore, deep models often depend on large, well-annotated datasets and require significant computational resources, posing barriers to real-world adoption in healthcare settings.

This study introduces an explainability-centered ECG classification framework designed to detect clinically significant cardiac events using deep learning. A modified EfficientNet-B0 architecture with Multi-Scale Attention (MSA) modules is employed to improve both local and global feature extraction from ECG images. The framework classifies inputs into four distinct classes: Myocardial Infarction, History of MI, Abnormal Heartbeat, and Normal ECG. To bridge the gap between AI predictions and clinical trust, the system incorporates visual explainability using Grad-CAM heatmaps and Integrated Gradients, alongside textual rationale describing model attention focus in anatomical terms. These additions enable medical professionals to understand the model's reasoning and assess prediction reliability more confidently.

The system further includes an intuitive, lightweight interface that enables real-time ECG image upload, prediction, and interpretability without requiring domain expertise. By offering both diagnostic accuracy and transparency, the proposed framework contributes to improved healthcare accessibility and diagnostic reliability. This work aligns with the United Nations **Sustainable Development Goal 3: *Good Health and Well-being***, by enhancing early detection of cardiovascular diseases and reducing dependency on scarce medical expertise in underserved regions.

The remainder of this paper is structured as follows: Section II presents the literature review. Section III details the system design and implementation methodology. Section IV discusses the experimental results and evaluation. Section V outlines the conclusion and potential future enhancements.

II. Literature Review

The automatic classification of myocardial infarction (MI) using electrocardiogram (ECG) data has significantly evolved with the advancement of deep learning. CNN-based models have demonstrated high performance in recognizing spatial patterns in ECG waveforms. Jian et al. proposed a multi-scale CNN (MSN-Net) that fuses independent lead-wise features, reaching a classification accuracy of 95.76% [1]. Cao et al. extended this by incorporating attention into a ResNet architecture to enable simultaneous MI detection and localization [2]. Chandra et al. employed a hybrid approach combining AlexNet and GoogLeNet, yielding high cross-dataset robustness [3]. A web-deployable platform, CARDIOBLINK, integrated real-time ECG analysis with a secure diagnostic interface, highlighting the practical deployment of such models [4]. Gustafsson et al. applied deep learning in emergency department settings for MI prediction, validating clinical feasibility in real-world conditions [5]. Models using sequential learning techniques, such as LSTM and Hidden Markov Models, have also been effective in capturing ECG rhythm irregularities related to MI and other cardiac conditions [6].

Transformers and fusion models have further enhanced ECG understanding. Vaid et al. introduced HeartBEiT, a vision transformer trained on millions of ECGs, which outperformed CNNs under data-constrained settings [7]. Tadesse et al. presented DeepMI, a deep fusion network capable of both MI classification and time-of-onset estimation [8]. Burman et al. explored CNN-LSTM models for ischemia detection, combining temporal rhythm and spatial pattern recognition [9]. Riek et al. developed ECG-SMART-NET to detect occlusion MI using a lightweight deep network suitable for constrained environments [10]. Davarmanesh et al. demonstrated the feasibility of using lead-I ECG for acute MI detection, emphasizing the potential of low-lead models [11]. Reviews by Xiong et al. and Abdar et al. comprehensively surveyed CNN, RNN, and hybrid model trends for MI and coronary artery disease classification, underscoring the importance of dataset diversity and model explainability [12], [13].

Interpretability remains a bottleneck for clinical integration. SHAP-based attribution has been integrated into arrhythmia-related ECG classifiers that include MI identification [6], while Grad-CAM and integrated gradients have been used to highlight waveform regions linked to MI features like ST-elevation or T-wave inversion [11]. To address the limitations of post hoc explanations, Tanyel et al. proposed a counterfactual-based framework (VCCE), which generates “what-if” visualizations of ECG changes responsible for a diagnosis, validated through expert interpretation scores [14]. While these contributions show strong promise, current models often rely on large annotated datasets, underperform on signal variations across demographics, and lack transparent, low-latency diagnostic pipelines. There is a growing need for unified frameworks that combine model accuracy, generalization, interpretability, and user-friendly deployment across clinical and remote settings.

Despite significant advances, several challenges remain in the domain of MI detection using ECG data. Many high-performing models depend on large, well-annotated datasets like PTB-XL, making them difficult to apply in low-resource or real-time scenarios. Generalizability across lead configurations, patient demographics, and acquisition devices remains limited, as most models are trained and evaluated on controlled datasets. While explainability has seen progress through techniques like Grad-CAM, SHAP, and counterfactuals, many approaches still lack clinical specificity or fail to align with cardiologists’ interpretive reasoning. Additionally, only a few studies integrate lightweight, real-time inference pipelines with robust interpretability, which is essential for deployment in wearable devices or emergency settings. The absence of unified frameworks that combine accuracy, transparency, efficiency, and deployment readiness highlights the need for end-to-end systems that can bridge the gap between research-grade models and practical clinical applications.

III. Methodology

This section outlines the methodology used to detect MI from ECG images. The approach has been illustrated in Fig. 1.

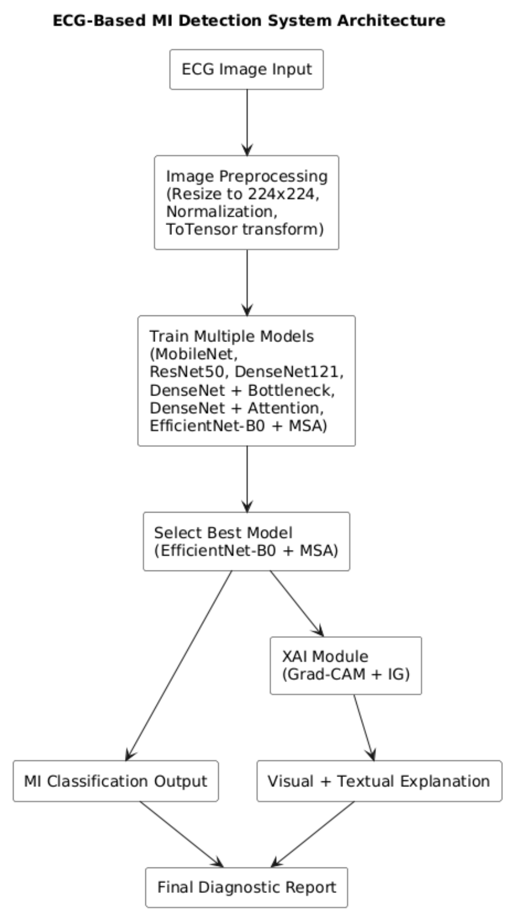


Fig. 1: System Architecture

A. Dataset Description

The "ECG Images Dataset of Cardiac Patients" [15] is a structured collection of electrocardiogram (ECG) images designed to support research and diagnostic advancements in cardiovascular medicine. It consists of 3951 images organized into four clinically distinct categories: myocardial infarction (MI), abnormal heartbeat, history of MI, and normal ECGs. These images are pre-segmented into individual leads and stored across training and testing directories. Specifically, the dataset includes 1195 images for MI patients (956 train + 239 test), 932 images for patients with abnormal heartbeat (699 train + 233 test), 688 images for individuals with a history of MI (516 train + 172 test), and 1136 images representing normal ECGs (852 train + 284 test). This multi-class structure provides a diverse and balanced foundation for training and evaluating ECG-based classification and anomaly detection models. The dataset supports the development of deep learning models for distinguishing between normal and pathological ECG signals. The MI category contains acute cardiac event patterns, while the history of MI and arrhythmic classes capture long-term and irregular activity, respectively. The normal class provides a reference baseline. This clinical separation allows for targeted model evaluation across both transient and chronic cardiac conditions. Additionally, the image format enables compatibility with explainable AI techniques such as Grad-CAM and integrated gradients, making the dataset well-suited for research in interpretable deep learning and automated ECG diagnostics.

B. Preprocessing

To prepare the ECG image dataset for model training, a standardized preprocessing pipeline was applied to ensure consistent input formatting and compatibility with deep learning architectures. Each ECG image was resized to 224×224 pixels and converted to a 3-channel RGB format to match the input requirements of pretrained convolutional neural networks such as EfficientNet-B0, MobileNet, and ResNet50. The images were then converted into tensors and normalized using standard ImageNet parameters (mean = [0.485, 0.456, 0.406], std = [0.229, 0.224, 0.225]).

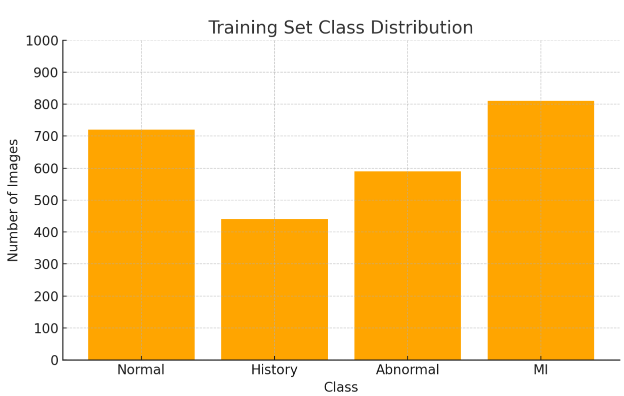


Fig. 2: Class Distribution of the dataset

Label encoding was performed based on the parent directory of each image, mapping each class (Myocardial Infarction, Abnormal Heartbeat, History of MI, and Normal) to a corresponding integer. Although the dataset was pre-divided into training and test sets, a manual validation split was performed by randomly allocating a fixed percentage (e.g., 10–15%) of samples per class into a separate validation set. An analysis of class distribution revealed a degree of imbalance, particularly between MI-related and normal ECG samples. This imbalance is visualized in Fig. 2. Rather than applying oversampling or augmentation, class imbalance was handled by computing inverse frequency-based class weights and incorporating them into the model's loss function. This approach ensured that underrepresented classes received proportionally higher importance during training, improving model sensitivity across all categories.

C. Baseline Models

To establish strong foundational benchmarks for ECG image classification, a range of baseline convolutional neural network (CNN) architectures were implemented and evaluated. These models were selected for their proven effectiveness in visual pattern recognition tasks and varying degrees of complexity, allowing for a comprehensive comparison across lightweight, mid-range, and deeper architectures. All models were trained using the same preprocessing pipeline, loss function (with class weights), and evaluation metrics to ensure fairness. The goal of this baseline phase was to identify the model family and depth most suited for ECG-based myocardial infarction (MI) detection before applying architectural enhancements such as attention modules or hybrid designs.

*1) **Baseline CNN**:* A custom CNN architecture was implemented using a series of convolutional, batch normalization, ReLU, and max-pooling layers. The model served as a minimal, parameter-efficient reference point. It included three convolutional blocks followed by a fully connected layer and softmax activation. While its simplicity enabled faster training, it lacked the representational depth to capture complex cardiac features effectively.

*2) **MobileNet**:* MobileNet was included as a lightweight baseline leveraging depthwise separable convolutions for reduced parameter count and computational efficiency. Its design made it suitable for deployment on resource-constrained environments such as mobile health devices. However, the trade-off in feature richness impacted its performance in distinguishing subtle MI patterns.

*3) **ResNet50**:* ResNet50 was used to evaluate a deeper residual network architecture that addresses the vanishing gradient problem through skip connections. Its 50-layer depth enabled extraction of high-level features critical for detecting morphological ECG anomalies. Among the baseline models, ResNet50 generally achieved higher accuracy, indicating its suitability for ECG image classification tasks.

*4) **DenseNet121**:* DenseNet121 was tested as another high-capacity model where each layer receives input from all preceding layers via dense connections. This architecture promoted feature reuse and improved gradient flow. DenseNet121 showed strong performance across most classes, but required longer training time and more memory due to its dense connectivity.

*5) **ConvNeXt-Tiny**:* ConvNeXt-Tiny was implemented to explore the potential of modern convolutional architectures that integrate design principles from vision transformers into CNNs. With features like large kernel sizes, inverted bottlenecks, and layer normalization, ConvNeXt brought architectural improvements over classical CNNs. Its performance was competitive with deeper networks while maintaining a relatively compact design, showcasing its adaptability to ECG image classification tasks.

D. Architectural Modifications

Following the baseline evaluation, three architectural enhancements were implemented to improve ECG classification performance by integrating deeper features and attention mechanisms. These modifications aimed to enrich feature extraction and boost model sensitivity to subtle cardiac abnormalities.

*1) **DenseNet121 with Bottleneck Refinement Block**:* The first modified model enhanced the standard DenseNet121 architecture by inserting a custom convolutional block after the final dense layer. This bottleneck-style refiner comprised a `Conv2D → BatchNorm → ReLU → Conv2D` sequence, followed by global average pooling and a final classification head. The goal was to refine high-level features by enabling deeper local processing before prediction. This addition helped capture more discriminative representations without significantly increasing model complexity.

*2) **DenseNet121 with Channel Attention**:* The second modification augmented DenseNet121 with a lightweight attention mechanism. A squeeze-and-excitation (SE) style attention block was inserted after the final convolutional feature map. It applied global average pooling followed by two dense layers and a sigmoid activation to produce channel-wise weights, which were multiplied back onto the feature map. This allowed the model to recalibrate its channel responses, boosting informative features and suppressing noise in the ECG signal representation.

*3) **EfficientNet-B0 with Multi-Scale Attention (EfficientNetMSA)**:* The third and most effective model was built on the EfficientNet-B0 backbone, enhanced by a custom-designed Multi-Scale Attention (MSA) mechanism to improve the model's ability to capture clinically relevant ECG patterns across varying feature depths. As illustrated in Fig. 3, the input ECG image (224×224×3) is first passed through the EfficientNet-B0 stem and early convolutional blocks, which extract low-level features such as edges and waveform shapes. From this backbone, three key sets of feature maps are extracted from progressively deeper layers:

- Block 3 captures intermediate spatial details,
- Block 4 extracts deeper semantic features,
- Block 6 captures high-level abstract representations.

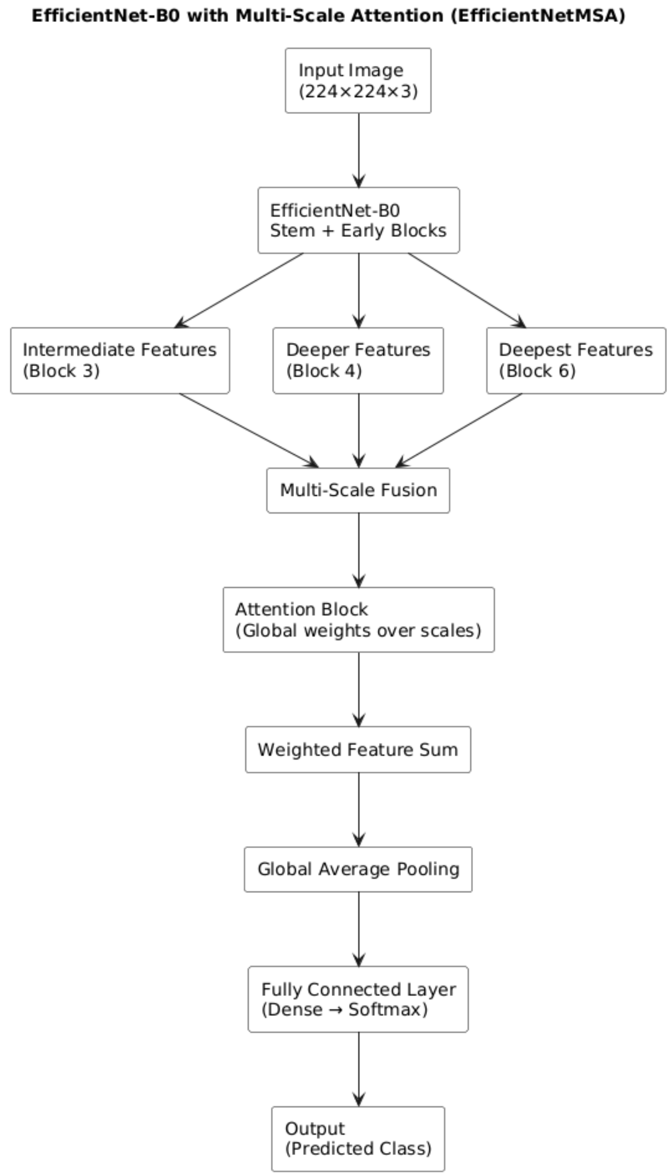


Fig. 3: Architecture of EfficientNet-B0 with Multi-Scale Attention

These multi-scale features are forwarded into the Multi-Scale Fusion module, where they are concatenated and passed into an Attention Block. This attention module performs global average pooling on each scale, then learns importance weights using a lightweight feedforward network. These learned weights are applied across the feature maps in the Weighted Feature Sum step, allowing the network to prioritize the most informative spatial-spectral features across scales. The aggregated features are then globally pooled and passed through a final fully connected layer with softmax activation to produce the predicted class label. This architecture effectively combines fine-grained patterns from shallow layers and abstract diagnostic signals from deeper layers, enabling robust detection of myocardial infarction and related cardiac conditions. The model achieved the highest classification accuracy among all evaluated architectures due to its balanced representation of local and global ECG features.

E. Training Settings

All models, including both baseline and modified architectures, were trained under consistent conditions to enable fair comparison. The following settings were applied across all experiments:

- Epochs: Each model was trained for 50 epochs, with early stopping applied based on validation loss to prevent overfitting.
- Batch Size: A mini-batch size of 32 was used for both training and validation phases.
- Optimizer: The **`Adam`** optimizer was used with an initial learning rate of 0.0001 and weight decay set to 1e-5 to encourage generalization.
- Loss Function: Weighted cross-entropy loss was used to address class imbalance. Class weights were computed inversely proportional to class frequencies in the training set.
- Dropout: A dropout rate of 0.3 was applied before the final fully connected layer in all models to reduce overfitting.
- Input Size: All ECG images were resized to 224×224×3 during preprocessing to match the input requirements of pretrained models.
- Pretrained Weights: All standard CNN models (MobileNet, ResNet50, DenseNet121, ConvNeXt) were initialized with ImageNet pretrained weights. Custom modifications (e.g., added attention or bottleneck layers) were trained from scratch on top of these backbones.
- Hardware: Training was conducted using a GPU-enabled environment with mixed precision where supported.

These training conditions ensured consistency across experiments and allowed the effect of architectural differences to be evaluated independently of tuning variance.

F. Evaluation Metrics and Visualization

Model performance was evaluated using a combination of quantitative and visual metrics. Accuracy, precision, recall, and F1-score were computed per class, with macro-averaging to ensure balanced evaluation across all categories. Confusion matrices provided insights into common misclassifications. Additionally, loss curves were analyzed over training epochs to assess convergence behavior and detect signs of overfitting. Explainability methods such as Grad-CAM and Integrated Gradients were also used to qualitatively validate whether the model focused on clinically relevant ECG regions during prediction.

G. Explainable AI

To support clinical interpretability and build trust in model predictions, two post-hoc visual explanation methods—Grad-CAM and Integrated Gradients—were incorporated into the system. In addition, a textual explanation generator was developed to describe the model's decision in human-readable terms. These explainability tools provided both qualitative and region-specific insights into how the model interpreted ECG images.

Grad-CAM (Gradient-weighted Class Activation Mapping) was used to highlight spatial regions in the ECG image that most strongly influenced the predicted class. The gradients flowing into the last convolutional layer were used to generate a heatmap, which was then overlaid on the original image. This allowed visual confirmation of whether the model attended to relevant waveform regions, such as elevated ST segments or T-wave inversions, particularly in myocardial infarction cases. Integrated Gradients was implemented to generate pixel-level attributions by integrating gradients along a path from a zero baseline image to the actual input. This method provided finer-grained saliency maps compared to Grad-CAM, revealing subtle changes in pixel intensity that contributed to the classification. It complemented Grad-CAM by offering a deeper look into how the input space affected the model's output. To further enhance interpretability, a textual explanation system was integrated using logic derived from the Grad-CAM heatmap. The hotspot region of the attention map (left, central, or right part of the image) was identified and mapped to class-specific templates. For example, if the predicted class was Myocardial Infarction and the attention region was central, the system generated a corresponding explanation describing how ST-elevation in that region is indicative of MI. Confidence scores were also appended to the explanation to aid in clinical decision-making.

IV. Results and Analysis

This section presents the performance evaluation of all baseline and modified models on the ECG classification task. Quantitative metrics such as accuracy, precision, recall, and F1-score are reported. The effectiveness of the proposed model modifications is highlighted, followed by qualitative insights from explainability outputs and training curve observations.

A. Performance of baseline models

TABLE I: Performance Comparison of Baseline Models

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Baseline CNN	0.72	0.70	0.68	0.69
MobileNet	0.48	0.39	0.43	0.38
ResNet50	0.68	0.65	0.64	0.62
DenseNet121	0.90	0.91	0.91	0.91
ConvNeXt-Tiny	0.26	0.06	0.25	0.10

Table I summarizes the classification performance of all baseline models on the ECG test set. Among the architectures evaluated, DenseNet121 achieved the highest scores across all metrics, with an accuracy of 90% and an F1-score of 0.91, indicating strong generalization and robustness in distinguishing between cardiac conditions. The custom Baseline CNN and ResNet50 also showed reasonable performance, though slightly lower in precision and recall. MobileNet, despite its efficiency, underperformed due to its reduced capacity for feature extraction. ConvNeXt-Tiny yielded the weakest results, likely due to underfitting caused by the limited dataset size and the model's architectural sensitivity to training scale. These results established DenseNet121 as the strongest candidate for further architectural enhancements.

B. Impact of Model Modifications

Table II presents the evaluation results of the three modified models designed to enhance ECG classification. All modified models achieved high accuracy above 91%, validating the effectiveness of the proposed enhancements. The DenseNet + Bottleneck model showed balanced performance with an F1-score of 0.91, while the DenseNet + Attention variant improved recall significantly to 0.99, indicating strong sensitivity to minority class patterns. The best performance was achieved by the EfficientNet-B0 + MSA model, which obtained the highest overall accuracy (96%) and F1-score (0.95). These results confirm that integrating multi-scale attention helped the model better capture relevant ECG features across different abstraction levels.

TABLE II: Performance Comparison of Modified Models

Model	Accuracy	Precision	Recall	F1 Score
DenseNet + Bottleneck	0.91	0.90	0.91	0.91
DenseNet + Attention	0.91	0.93	0.99	0.96
EfficientNet-B0 + MSA	0.96	0.94	0.97	0.95

C. Explainability Outputs

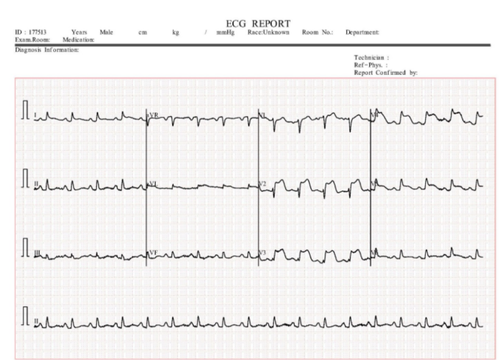
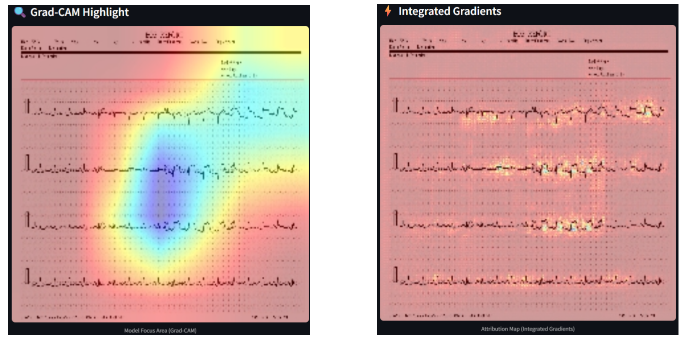


Fig. 4: Sample Input

Figs. 5a and 5b present the explainability outputs generated by the best-performing model (EfficientNet-B0 with Multi-Scale Attention) on the sample image in Fig. 4. The Grad-CAM heatmap highlights the central region of the ECG image, indicating that the model focused on a segment where significant waveform abnormalities, such as ST elevation, may be present. This attention aligns well with the clinical indicators of myocardial infarction. The Integrated Gradients overlay provides a more fine-grained attribution by emphasizing specific pixel-level contributions along the waveform. Together, these visual explanations confirm that the model's predictions are based on diagnostically relevant features, thereby increasing trust and interpretability in clinical settings.



(a) Grad-CAM Output (b) Integrated Gradients Output

Fig. 5: Explainability visualizations using Grad-CAM and Integrated Gradients on ECG image

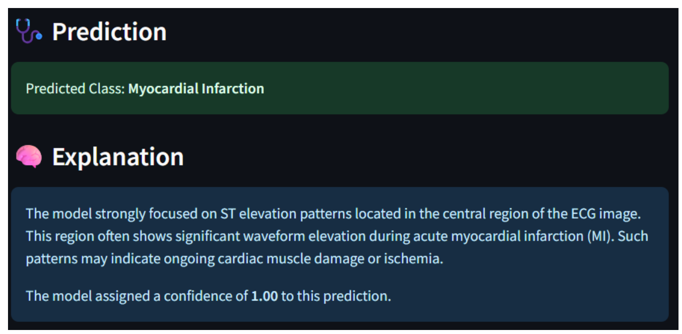
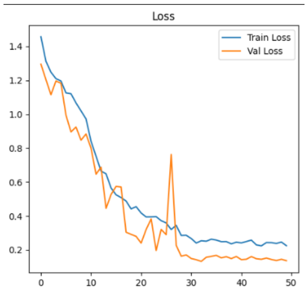


Fig. 6: Textual explanation for sample ECG

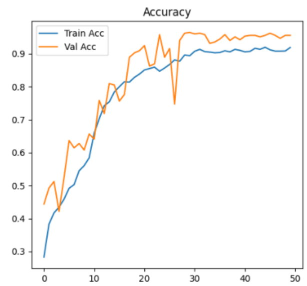
Fig. 6 presents an example output from the explainable AI module for the sample input 4. The predicted class is Myocardial Infarction, and the associated explanation highlights the central region of the ECG image as the primary area of interest. The model correctly identified waveform elevations in this region, typically indicative of ST-elevation myocardial infarction and provided a confidence score of 1.00. This form of interpretation supports diagnostic clarity and reinforces trust in model decisions.

D. Training & Accuracy Curves

Figure 7 shows the training and validation loss and accuracy curves for the best-performing model, EfficientNet-B0 with Multi-Scale Attention. The training loss decreased steadily over the 50 epochs, while the validation loss exhibited minor fluctuations but maintained a downward trend, indicating consistent generalization without overfitting. Validation accuracy rapidly improved and remained stable above 95%, even outperforming training accuracy in later epochs. This gap reflects strong generalization and the effectiveness of regularization techniques such as dropout and class-weighted loss during training.



(a) Training and Validation Loss



(b) Training and Validation Accuracy

Fig. 7: Training curves for EfficientNet-B0 with Multi-Scale Attention

E. User Interface

A user-friendly web interface was developed using Streamlit to enable intuitive interaction with the ECG classification system. The interface includes user authentication, ECG image upload, and visualization of prediction results with explainable outputs.

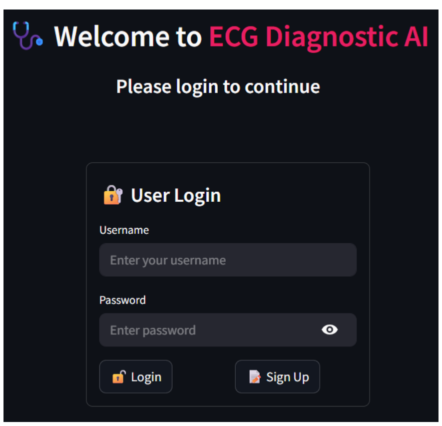


Fig. 8: Login Page

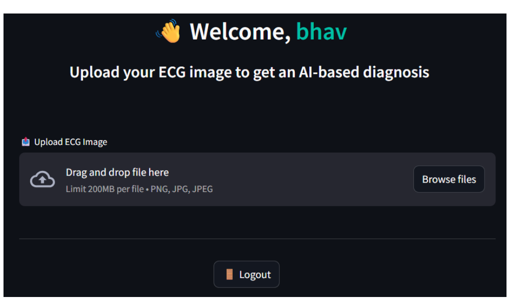


Fig. 9: UI to upload an ECG

Upon launching the application, users are presented with a secure login screen (Fig. 8). The interface supports both login and sign-up functionality, ensuring that access to the diagnostic system is personalized and secure. New users can create an account, while existing users can log in using their credentials to proceed to the prediction dashboard. After successful authentication, users are welcomed by name and prompted to upload an ECG image for diagnosis (Fig. 9). The system supports common image formats such as PNG and JPEG, with a file size limit of 200MB. Once an image is uploaded, the model processes it and returns the predicted class along with Grad-CAM and Integrated Gradients visual explanations. The system also generates a confidence score and textual rationale based on the model's focus region.

V. Conclusion

This work presents an explainable deep learning framework for classifying ECG images into clinically meaningful categories, with a focus on detecting myocardial infarction. Multiple baseline models were implemented and compared, followed by three architectural enhancements aimed at improving performance. The best results were achieved using an EfficientNet-B0 model augmented with multi-scale attention, reaching an accuracy of 96%. Integrating Grad-CAM, Integrated Gradients, and textual explanations provided interpretable outputs that enhanced clinical trust and diagnostic support. The system was wrapped in an intuitive Streamlit-based interface, making the model accessible for real-time ECG analysis.

Future improvements can focus on expanding the dataset to include more patient diversity and additional cardiac conditions such as atrial fibrillation and bundle branch blocks. Fine-tuning transformer-based models or exploring hybrid CNN-ViT architectures may further improve classification accuracy. Real-world deployment could benefit from incorporating PDF or raw ECG input support, allowing direct integration with hospital systems. Lastly, incorporating feedback loops from clinical experts could help refine the model explanations and align them more closely with cardiologist decision-making.

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