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Automated Myocardial Infarction Detection Using Hilbert Transform And Residual Networks

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Abstract: Myocardial infarction (MI) remains one of the leading causes of mortality worldwide.. In this study, we present an automated deep learning-based approach for MI detection using the PTB-XL ECG dataset. The raw ECG signals were first processed using the Hilbert Transform to emphasize the analytic components and enhance signal representation. Subsequently, the transformed signals were converted into time-frequency spectrograms, allowing the exploitation of both spectral and temporal information. To classify, we developed and trained a deep convolutional neural network incorporating Residual Networks (ResNet) architecture, which addresses the vanishing gradient problem . The model achieved promising results, with high accuracy, sensitivity, specificity, F1-score, and AUC, indicating its potential for reliable MI detection. This work demonstrates the value of combining advanced signal processing techniques with deep learning for automated cardiac diagnosis.

***Index Terms* - Component, formatting, style, styling, insert.**

Introduction

Heart disease remains one of the leading causes of death worldwide, silently affecting millions of people each year. It often develops over time, influenced by lifestyle factors like unhealthy diet, absence of exercise, smoking, and stress, as well as medical conditions like blood sugar or hypertension. Cardiac disease includes a narrowing or Restricted blood flow that supply the heart muscle with oxygen and nutrients. When these vessels become too clogged, the heart struggles to function properly [1]. In 2021, cardiovascular diseases (CVDs) accounted for approximately 19.91 million deaths worldwide . In India, the burden is particularly significant, with cardiac disease being the leading cause of death among women, exceeding all forms of cancer combined[2].

Myocardial infarction, or heart attack, happens when one of any critical arteries becomes completely blocked, cutting off the blood flow to a part of the heart. Without oxygen, that part of the heart muscle begins to die. It often strikes without warning, with symptoms such as chest pain, difficulty in breathing, cold sweats, or pain radiating to the arm. Not everyone experiences these signs , especially women or older adults. A heart attack isn’t just a momentary event , it can leave lasting hurt to the heart and even be life threatening [3]. Globally, the prevalence of MI varies with age: approximately 3.8\% in individuals under 60 years and 9.5\% in those over 60 . In the United States, it's estimated that someone experiences a heart attack every 40 seconds [4].

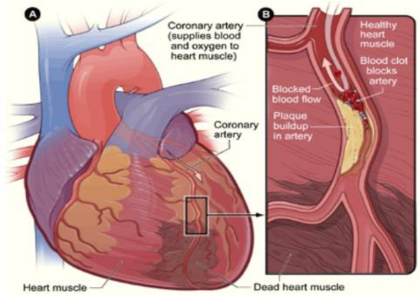

Figure 1: Blood clot blocks in the heart

Recovery from a heart attack is deeply personal. It may involve medications, lifestyle changes, or surgical procedures like stents or bypass surgery. Many survivors face anxiety, fear of recurrence, or changes in daily life. With the right care, support, and a renewed commitment to heart health, many people live full and active lives after a heart attack. Understanding myocardial infarction isn't just about knowing the biology. It's about recognizing the importance of listening to your body and making heart-healthy choices every day. Survival rates after a heart attack have improved over time. With current estimates indicating an overall survival rate of around 87.5\% . However, recovery is not solely about survival; it often involves significant lifestyle changes, emotional adjustments, and ongoing medical care. In India, the increasing prevalence of heart disease has led to a surge in related insurance claims, reflecting both the health and financial impacts of this condition [5].

A myocardial infarction doesn't come with a dramatic warning. it can begin subtly, almost quietly, before becoming life-threatening. One of the most common symptoms is chest pain or discomfort. This is described as a pressure, or squeezing sensation in the center or left side of the chest. It's not always severe. Chest pain isn't the only red flag. Pain or discomfort can also spread to the arms (especially the left), back, neck, jaw, or stomach. Other warning signs include shortness of breath, cold sweat, nausea, lightheadedness, or a sudden feeling of fatigue. Women may experience symptoms that are harder to recognize, such as unusual tiredness, anxiety, or indigestion-like discomfort, making it easy to misattribute the cause [6].\\
The causes of MI are high blood pressure, high cholesterol, smoking, diabetes, obesity, lack of physical activity, and chronic stress. A diet high in saturated fats, salt, and sugar also plays a role. Genetics is an important factor. Age increases risk, especially in men over 45 and women over 55, but younger people are not immune, especially if they live with multiple risk factors[7].
\\To get a clearer picture, doctors may also perform imaging tests like echocardiography (ultrasound of the heart), coronary angiography, or a chest X-ray. These tests help confirm the diagnosis and also show how much of the heart has been affected. In some cases, CT or MRI scans may be used for detailed insights[8]. An Electrocardiogram is a fast , non-invasive exam which monitors the electrical activity of the heart. Each heartbeat is controlled by an electrical signal that begins in the heart's natural pacemaker (the sinoatrial node). An ECG records these signals as waves on paper or a screen, allowing healthcare professionals to see how the heart is functioning in real-time[9].

I. Related Works

In [10], a two-dimensional Convolutional Neural Network (2D-CNN) was developed to classify electrocardiogram (ECG) signals into eight distinct categories which are normal beats, premature ventricular contractions, paced beats, right and left bundle branch blocks, atrial premature contractions, ventricular flutter waves, and ventricular escape beats. One-dimensional ECG time series data were first transformed into two-dimensional spectrograms using short-time Fourier transform (STFT). This 2D-CNN architecture consists of four convolutional and four pooling layers. This model extracted meaningful features from these spectrograms. Evaluation using the MIT-BIH arrhythmia dataset demonstrated a high average classification accuracy of 99.11\%. \\
In [11], researchers proposed an Enhanced Deep Learning-based Convolutional Neural Network (ED-CNN) for improving diagnostic outcomes for heart disease. This advanced architecture integrates a multi-layer perceptron enhanced by regularization learning. This reduce feature dimensionality, thus optimizing classification speed and accuracy. The ED-CNN framework was implemented within an Internet of Medical Things (IoMT) platform. This provides cloud-based decision support tools to assist healthcare professionals

in diagnosing cardiovascular conditions. Comparative testing showed that ED-CNN outperformed traditional methods such as Artificial Neural Networks (ANN), Deep Neural Networks (DNN), Recurrent Neural Networks (RNN), Ensemble Deep Learning Smart Healthcare Systems (EDL-SHS), and Neural Network Ensemble (NNE), achieving a precision of up to 99.1\% when appropriately tuned.\\
In [12], a context-aware authentication system leveraging wearable devices was introduced. This system utilizes soft biometric indicators such as heart rate, gait patterns, and breathing sound signals . By employing the k-Nearest Neighbor (KNN) algorithm, the method achieves high accuracy while maintaining a seamless user experience. The aim is to provide an implicit authentication process that operates unobtrusively. In [13],author surveyed different machine learning algorithms for MI detection. From this Convolutional Neural Network (CNN)-based model was proposed for the classification of various ECG arrhythmias. The categories of diseases are supraventricular ectopic, non-ectopic, fusion, ventricular ectopic, and unknown beats, aligned with the AAMI EC57 standard. This method was validated using SVEB and VEB classes from the MIT-BIH arrhythmia dataset.

II. PROPOSED METHOD

This paper proposes a novel system for detecting myocardial infarction (MI) from ECG signals. This approach aims to capture both the temporal and spectral features of ECG signals, enhancing the accuracy and robustness of MI diagnosis. This is by combining time-frequency analysis using spectrograms and Hilbert Transform, followed by classification through deep learning models.

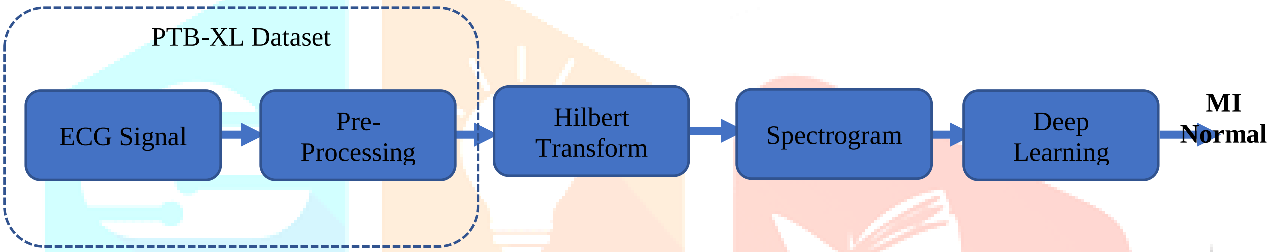

Figure 2 : Block diagram of the proposed system

The PTB-XL ECG dataset is one of the largest and most comprehensive collections of clinical ECG recordings publicly available. It includes 21,799 12-lead ECG records gathered from 18,869 different patients. , Each signal has a duration of10 seconds long. These recordings have been carefully reviewed and annotated by one or two expert cardiologists. In total, the dataset includes 71 unique ECG statements, based on the SCP-ECG standard. This covers a range of diagnostic categories such as heart rhythm, waveform shape, and possible heart conditions. The creators have also provided standardized training and testing splits. This helps ensure consistency and fairness when comparing different algorithmic approaches. Beyond the ECG recordings themselves, the dataset is enriched with detailed metadata. The metadata contains patient demographics, heart attack indicators, diagnostic label probabilities, and signal characteristics[14].

A Hilbert Transform

The Hilbert Transform is a fundamental mathematical tool in signal processing obtain the analytic representation of a real-valued signal. The key idea is that it provides a way to construct a complex signal by shifting its phase by 90 degrees. This transformation allows us to generate the Hilbert transform pair. This is widely used in applications like signal modulation, envelope detection, and instantaneous frequency analysis[15].

The Hilbert transform of a signal x(t) is defined as the convolution of x(t) with the function $1/\pi t$. This operation is expressed as:

$$\hat{x}(t) = 1/\pi * \text{P.V.} \int \text{from } -\infty \text{ to } \infty \, (x(\tau) / (t - \tau))\, d\tau$$

where P.V. stands for the Cauchy principal value, used to handle the singularity at $t = \tau$. This integral essentially captures the behavior of the signal in the frequency domain and shifts its phase by 90 degrees. This will creat a complex signal.

The result of applying the Hilbert transform is a signal $\hat{x}(t)$ that is quadrature to the original signal x(t). This is a shifted version of x(t). By combining x(t) with its Hilbert transform $\hat{x}(t)$, complex signal z(t) is obtained.

$$z(t) = x(t) + j\hat{x}(t)$$

where j is the imaginary unit. This complex signal has both the original signal's information and its analytic counterpart. This allows for easier analysis of properties like instantaneous amplitude and phase.

B Spectrogram

A spectrogram is a visual representation of how the frequency content of a signal evolves over time. It shows how the energy of different frequency components of a signal is distributed across time. This it becomes a powerful tool for analyzing non-stationary signals such as speech, music, and biomedical data.

To compute a spectrogram, the signal is divided into small overlapping segments. Each segment is analyzed using the Short-Time Fourier Transform (STFT). The STFT applies the Fourier Transform to each segment by giving a time-localized frequency representation.

To compute a spectrogram, the signal is divided into small overlapping segments. Each segment is analyzed using the Short-Time Fourier Transform (STFT). The STFT applies the Fourier Transform to each segment by giving a time-localized frequency representation. The STFT of a signal x(t) is given by:

$$STFT\{x(t)\}(\tau, \omega) = \int x(t)w(t - \tau) e^{(-j\omega t)} dt$$

where $w(t - \tau)$ is a window function centered at time τ. This window function ensures that only a portion of the signal around τ is considered when computing the Fourier transform,. It preserves time information.

The magnitude squared of the STFT gives the spectrogram:

$$Spectrogram(\tau, \omega) = |STFT\{x(t)\}(\tau, \omega)|^2$$

This 2D representation is often color-coded to indicate the intensity (power) of frequency components. Brighter colors typically represent higher energy at a given frequency and time. Spectrograms are widely used in various domains, including speech recognition, music analysis, sonar, radar, and medical diagnostics. They help in identifying transient events, frequency shifts, and other time-varying features of signals.

3.4 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a class of deep learning models primarily used for processing data with a grid-like topology. They are designed to automatically and adaptively learn spatial hierarchies of features through backpropagation by using multiple building blocks. The blocks included convolution layers, pooling layers, and fully connected layers.

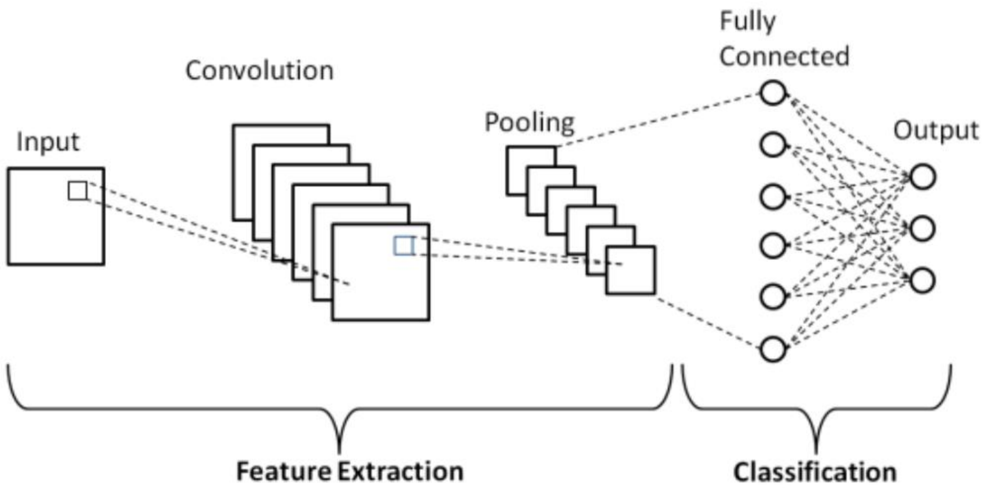

Figure 3: CNN Architecture

The core operation in a CNN is the convolution. This involves a small matrix of weights which is known as a filter or kernel. The kernels is slid over the input data. This operation captures local features, such as edges or textures, and produces a feature map. Deriving it mathematically it is difficult. For simplicity , 2D convolution of an image I with a filter K is defined as:

$$S(i, j) = (I * K)(i, j) = \sum\sum I(m, n) K(i - m, j - n)$$

The filter is applied at each position of the input to compute a weighted sum of the local region. This allows the CNN to identify important patterns regardless of their position in the image. This will repeat for entire image. After convolution, an activation function (commonly ReLU) is applied to introduce non-linearity. Pooling layers reduce the spatial size of the feature maps and make the representations more manageable. Pooling also helps in making the network more effective to slight translations in the input. One or more fully connected layers are used to combine features and perform classification or regression. CNNs are widely used in computer vision tasks such as image classification, object detection, and image segmentation, but their principles are also applicable in fields like audio processing and medical signal analysis.

3.5 Residual Networks (ResNet)

Residual Networks, or ResNets, are a type of deep neural network architecture that addresses the problem of vanishing gradients in very deep networks. This was Introduced by Microsoft Research in 2015. ResNets made it possible to train networks with hundreds or even thousands of layers . The novel concept is called residual learning.

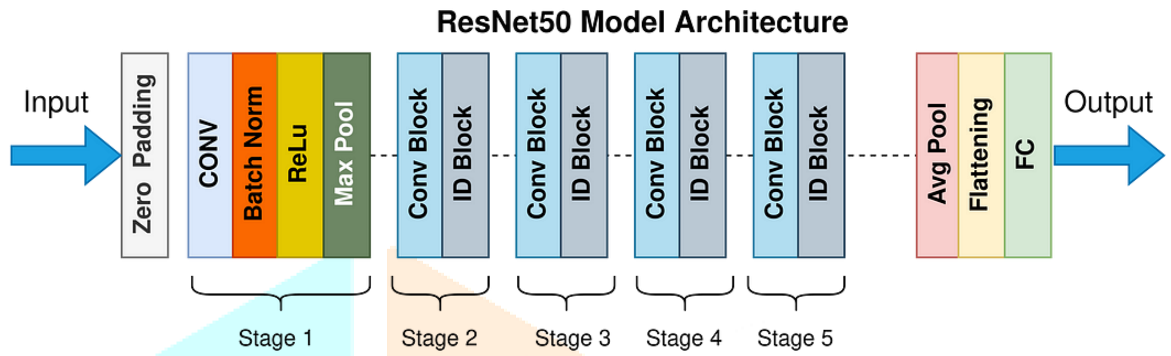

Figure 4: Resnet Architecture

The key idea in ResNet is the introduction of shortcut connections, also known as skip connections. This bypass one or more layers. Instead of trying to learn the underlying mapping directly, the network learns the residual. The difference between the input and the desired output. This can be mathematically represented as:

$y = F(x) + x$

Here, x is the input to a set of layers,. F(x) is the output after passing through those layers. y is the final output after adding the original input back. This simple addition helps preserve the gradient during backpropagation, making training deep networks more feasible.

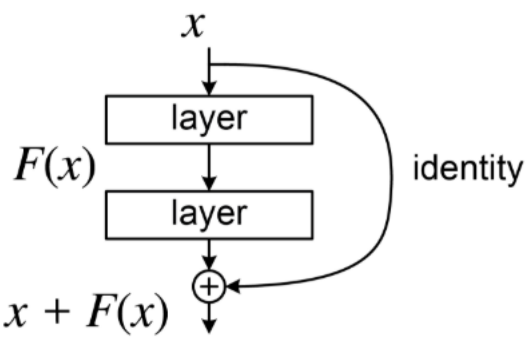

Figure 5: Residual Block with Skip Connections

A basic building block of ResNet consists of two or three convolutional layers followed by batch normalization and ReLU activation, with a shortcut connection . This short cut connection adds the input to the output. These blocks are stacked to form very deep architectures like ResNet-18, ResNet-50, or ResNet-101, where the number refers to the number of layers in the model.

ResNets have become a backbone in many computer vision tasks due to their performance and stability. They are widely used in image classification, object detection, medical image analysis. The success of ResNet has also influenced the design of many subsequent architectures in deep learning.

III. PROPOSED METHOD

All experiments were conducted using Google Colab, which provides a cloud-based Jupyter notebook environment. Python language was used for programing. To accelerate deep learning model training, we utilized the *NVIDIA Tesla T4 GPU** offered through Colab Pro GPU tier. The T4 GPU supports mixed precision computation, which helped reduce training time and improve efficiency.The use of cloud-based GPU resources ensured reproducibility and accessibility for deep learning experiments. we employed the WFDB (WaveForm DataBase) Python library for ecg data analysis. This is specifically designed for reading, writing, and processing physiologic signal data.

Key functions used from the WFDB library include:

wfdb.rdrecord() – Loads raw ECG signals and metadata from .dat and .hea files.

wfdb.plot_wfdb() – Visualizes ECG recordings directly in the notebook.

wfdb.rdheader() – Reads header information for signal configuration.

This library enabled efficient access to multi-lead ECG signals. It also allowed easy synchronization with annotations provided in the dataset.

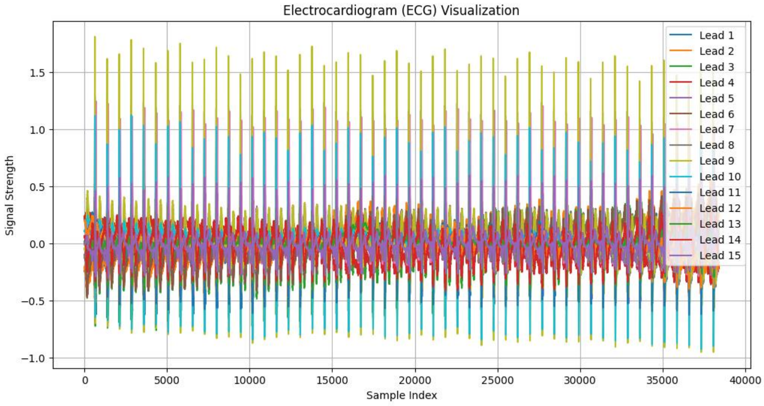

Figure 6: Visualization an ECG signal of PTBXL dataset

To evaluate the effectiveness of our proposed myocardial infarction detection framework, we conducted a series of experiments using the publicly available PTB-XL dataset. This dataset is well-suited for arrhythmia and myocardial infarction detection due to its size, quality, and labelling. Each ECG signal was first pre-processed by applying a Hilbert transform. This allowed us to derive the analytic signal and capture the instantaneous amplitude and phase components. This transformation enhances the signal's interpretability in the time-frequency domain. This is especially for transient patterns associated with myocardial infarction.

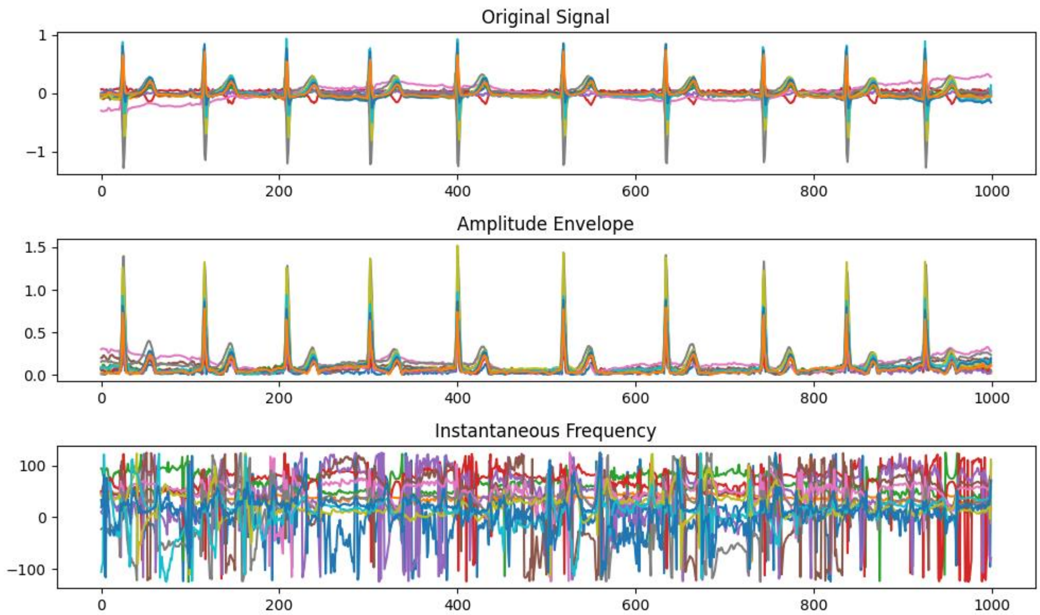

Figure7: Output waveform of Hilbert transform

For convolutional neural networks, we converted 1D ECG signals into a 2D visual format suitable. So we generated spectrograms using short-time Fourier transform (STFT). These spectrograms visually represent the energy distribution of the signal over time and frequency This makes it easier for deep learning models to capture complex signal patterns.

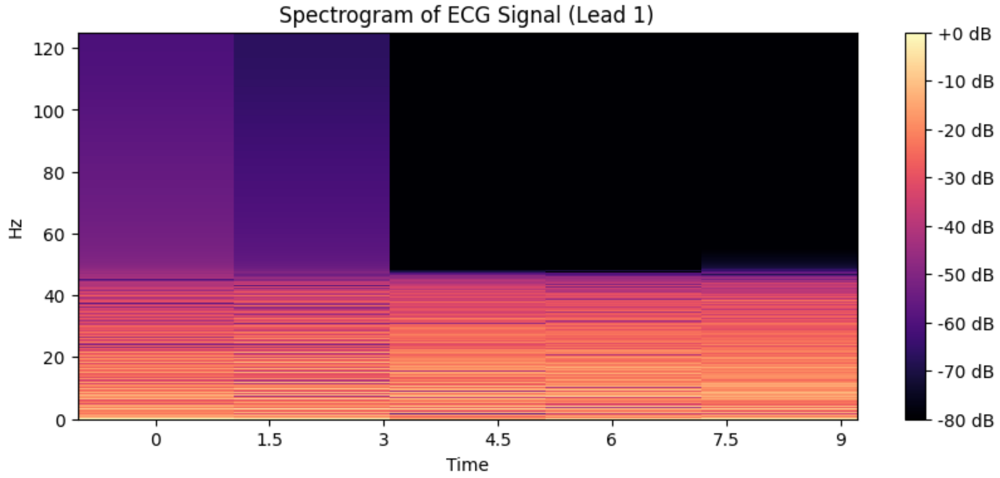

Figure 8: Spectrogram of an ECG signal after applying Hilbert transform

We experimented with two deep learning architectures. A custom CNN model designed with multiple convolutional and pooling layers to automatically extract spatial and frequency-domain features from spectrogram images. A ResNet-based model, adapted from ResNet-18, which incorporates residual connections to facilitate deeper learning while avoiding the vanishing gradient problem. This architecture has shown strong performance in image-based medical tasks. Both models used ReLU activation functions, batch normalization, and dropout layers to improve generalization.

The dataset was split into three subsets:

Training set (70%): Used to learn model parameters.

Validation set (15%): Used during training to monitor overfitting and tune hyperparameters.

Test set (15%): Used for final performance evaluation.

The split was stratified based on the diagnosis labels to ensure class balance across all sets.

All models were trained using the Adam optimizer, with an initial learning rate of 0.001. We employed early stopping based on the validation loss to prevent overfitting. The batch size was set to 32, and training was conducted for a maximum of 50 epochs.

To fine-tune the model, we performed a grid search over key hyperparameters including:

Learning rate ([0.0001, 0.001, 0.01])

Number of convolutional layers

Dropout rate ([0.3, 0.5, 0.7])

Kernel size ([3x3, 5x5])

The best-performing model was selected based on the highest validation accuracy and lowest validation loss.

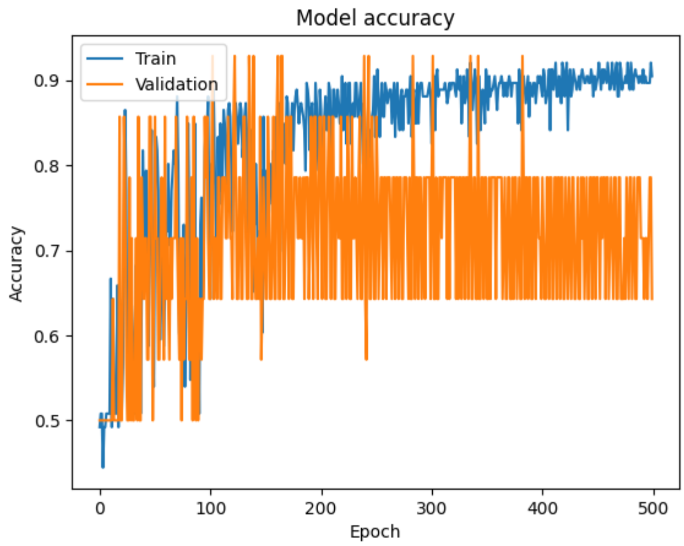

Figure 10: Training History

To evaluate the effectiveness of the myocardial infarction detection models, we used different standard classification metrics. Below are the mathematical definitions and explanations for each.

Let the confusion matrix consist of the following:

- TP (True Positive): Correctly predicted positive cases (MI correctly identified)
- TN (True Negative): Correctly predicted negative cases (non-MI correctly identified)
- FP (False Positive): Incorrectly predicted positive cases (non-MI identified as MI)
- FN (False Negative): Incorrectly predicted negative cases (MI identified as non-MI)

Accuracy measures the overall correctness of the model by showing the proportion of correctly classified cases out of all predictions.

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Sensitivity, also known as recall or true positive rate, evaluates the model's ability to correctly identify positive cases (i.e., myocardial infarction).

Sensitivity = TP / (TP + FN)

Specificity measures the proportion of actual negatives (non-MI) correctly identified by the model. It is also referred to as the true negative rate.

Specificity = TN / (TN + FP)

The F1-Score is the harmonic mean of precision and recall. It balances the trade-off between the two, especially useful when dealing with imbalanced datasets.

F1-Score = 2 × (Precision × Recall) / (Precision + Recall), where Precision = TP / (TP + FP)

AUC is calculated from the Receiver Operating Characteristic (ROC) curve, which plots the True Positive Rate (Sensitivity) against the False Positive Rate (1 – Specificity). AUC represents the model's ability to distinguish between classes. A higher AUC indicates better discriminatory performance.

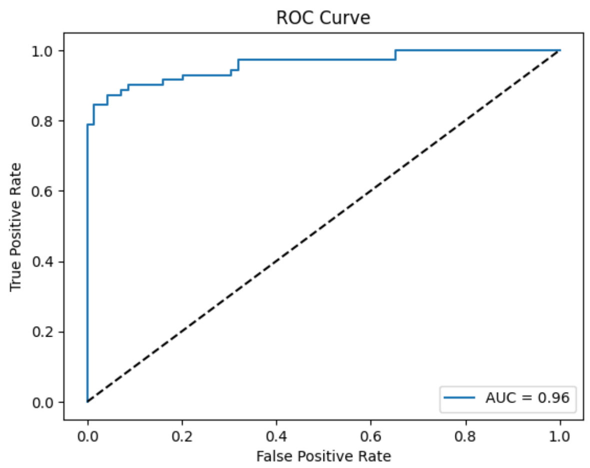

Figure 10: ROC Curve

Table I : Performance of the algorithms

Method	Accuracy	Sensitivity	Specificity	F1 Score	AUC
CNN[37]	0.72	0.636	0.602	0.611	0.877
SincNet[37]	0.73	0.666	0.589	0.6	0.884
CNN with Entropy features [37]	0.765	0.714	0.662	0.68	0.910
Proposed Method	0.8571	0.9155	0.7971	0.852	0.9589

CONCLUSION AND FUTURESCOPE

In this paper, we proposed a deep learning based framework for the detection of myocardial infarction using the PTB-XL ECG dataset. By applying the Hilbert transform and converting the ECG signals into spectrograms, we were able to leverage both temporal and frequency features. Two models were trained and evaluated. The models demonstrated a better performance in terms of accuracy, sensitivity, specificity, F1-score, and AUC. These results indicate the effectiveness of using hilbert -based transform in deep learning for automated myocardial infarction detection.

Although the current system gave good results, there is still scope of improvement. Future work can explore several ideas to enhance performance and usability. One option is to add attention mechanisms, which can help the model focus on the most important parts of the ECG signals. Another direction is to expand the dataset by including recordings from different hospitals and a more diverse range of patients. Testing the model in real-time environments could also improve its practical value. In addition, combining ECG data with other patient information, such as age, gender, or medical history, may lead to more accurate predictions. Applying explainable AI methods will help make the model's decisions easier to understand. This can build trust among users and medical professionals.

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