

ECG Image Classification for Heart Disease Detection Using a Hybrid EfficientNet-ViT Model

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Abstract - Timely medical action applied on early and correct identification of cardiac disease. Although manual interpretation of electrocardiography (ECG) can be personal and time-consuming, it is essential in order to diagnose cardiac problems. Deep learning developments have made automated techniques for ECG analysis possible, increasing the precision and effectiveness of diagnosis. This study uses a deep learning model with a hybrid approach that combines Vision Transformer (ViT) and EfficientNet to present a real-time ECG image recognition system. ViT enables robust classification by capturing global interdependence in the ECG signals, whereas EfficientNet is utilized for the abstraction of spatial features. The ECG scans are separated into four categories in the dataset categories: Normal, Abnormal Heartbeat, History of Myocardial Infarction (MI), and Patients with Myocardial Infarction. The categorization is given as a binary job that separates the being of heart disease from normal conditions in order to simplify real-time implementation. The suggested model showed excellent precision as fit as effectiveness in differentiating between normal and pathological ECG patterns after being trained and evaluated on a sizable dataset. Comprehensive tests show that compared to conventional CNN-based designs, the hybrid technique greatly improves performance. The model is a great contender for practical implementation in clinical settings due to its strong generalization across different ECG patterns. Our test findings support the viability of this method for detecting cardiac illness in the moment, which might be beneficial with early diagnosis and prompt treatment. Enhancing the model's interpretability and expanding its use to intelligent health monitoring gadgets are the goals of future research.

Keywords—ECG, Deep Learning, EfficientNet, Vision Transformer, Hybrid Model, Real-Time Detection

I. INTRODUCTION

Heart disease continues to be among of the world's top causes of death, impacting millions of people annually. Arrhythmias, myocardial infarction (MI), and other

cardiovascular illnesses that have the potential to create major health issues or even death are included in this category. In instruction to improve patient care and avoid serious consequences, early diagnosis of these illnesses is essential. A popular non-invasive diagnostic technique that tracks the heart's electrical activity over time is electrocardiography (ECG). Yet, physicians' human interpretation of ECG data is frequently arbitrary, subject to human error, and necessitates a high level of skill. Automated techniques utilizing machine learning (also known as AI) have become crucial in facilitating prompt and precise diagnostics due to the growing amount of patient data. Recent developments in deep learning, namely in the areas of Vision Transformers (ViT) and Convolutional Neural Networks (CNNs), have shown great promise in medical picture categorization problems. ViTs provide better global feature understanding while CNNs are better at extracting local features, which makes them perfect for ECG analysis. The capabilities of ViT, which recognizes long-range correlations in images, and EfficientNet, a CNN-based architecture renowned for its computing efficiency, are combined in this research to present a novel hybrid technique. The goal of this project is to make a reliable and accurate real-time ECG Heart disease categorisation system detection by utilizing both architectures. In order to provide real-time medical decision support, the suggested method divides ECG separated into four categories and then subsequently simplifies into a classification that is binary mechanism capable of distinguishing between normal and abnormal cardiac diseases. The purpose of this study is to develop a deep learning algorithm that is scalable, effective, and extremely accurate so that medical personnel may quickly diagnose cardiovascular disorders. Patient outcomes may be improved by integrating this system with wearable monitoring technology or clinical procedures, which could allow for constant surveillance of patients and early intervention. Furthermore, we may improve the model's generalization across various patterns of ECG and datasets by utilizing transfer learning strategies and pre-trained models. Comprehensive tests and evaluations are conducted utilizing a large dataset to get a advance validate the system. To improve diagnostic efficiency, the study also investigates the possibility of implementing this

approach in cloud-based medical solutions, which would enable smooth integration with hospital administration systems. This study offers a workable and efficient answer to most important problems in cardiovascular healthcare, contributing to the continuous developments in AI-driven medical applications.

II. LITERATURE REVIEW

Recurrent neural networks, or RNNs, and CNNs are two examples of deep learning networks which have been used for ECG categorization. CNNs like ResNet and MobileNet have proven to be successful in medical image processing in recent studies. ViT may record global dependencies, which makes it appropriate for ECG image classification, while CNNs mostly concentrate on local characteristics. In order to capitalize on each architecture's advantages and increase accuracy, this study combines them.

Recent developments in transfer learning and deep learning network that as given encouraging outcomes in detecting cardiovascular illness. According to a thorough analysis by Sunil Kumar with Kumaresan [1], transfer learning models gives conventional network, machine learning method for the reorganization of the cardiovascular illness, with accuracy values of above 96%. Similar to this, Golande with Pavankumar [2] suggested a hybrid deep-learning model for ECG-based cardiac disease prediction that combines CNN and LSTM, showing notable gains in classification effectiveness and error reduction. The usage of vision transformer models, like Google-ViT and Swin-Tiny, for ECG image classification was investigated by Kilimci et al. [3] in another work. They achieved impressive classification results that outperformed those of conventional deep learning architectures. Furthermore, ECGConVT, a hybrid CNN and ViT-based structure for ECG picture classification, was presented by Khalid et al. [4]. It demonstrated the possibility of merging CNNs and transformers for improved feature extraction and got an accuracy of 98.5%. With an accuracy of 96.22%, Jothiaruna [5] also used EfficientNet to classify cardiovascular illness on ECG images, emphasizing the significance of hyperparameter tweaking in deep learning-driven medical image analysis.

Recent advancements in deep learning method and machine learning have led to significant advancements in the estimate of cardiac disease, with a different types of methods and algorithms improving interpretability and accuracy. To achieve 88.5% classification accuracy, Karthick et al. [6] used a different kind of techniques, like SVM, the Gaussian Naive Bayes method (GNB), logarithmic regression (LR), LightGBM, which the XGBoost and RF. Their results highlighted the need for hyperparameter adjustment while highlighting the effectiveness of tree-based models like RF and XGBoost in processing intricate medical data. By combining recurring layer for time data analysis and layers of convolution for feature extraction, Al Reshan et al. [7] presented an innovative HNN using deep learning method for the prediction of heart disease. This hybrid architecture is a promising clinical decision support tool since it greatly increased classification accuracy and found minor risk variables that traditional approaches frequently miss. In order to ensure resilience against noisy and insufficient information, Almazroi

et al. [8] created a system to support clinical decisions for cardiac disease prediction that is optimized for huge-scale medical datasets. Their methodology demonstrated a high degree of suitability for real-time diagnosis applications, hence highlighting the significance for data preparation in medical artificial intelligence systems.

RoBERTa achieved the greatest F1 score around 93% in a study by Khan et al. [9] that looked at nine models based on transformer for tweet classification related to health. Their research demonstrated the transformer models' potential for use in resource-constrained healthcare environments by highlighting their scalability. For predicting heart disease (CVD) risk variables using electronic health records (EHRs), Poulain et al. [10] suggested a transformer-based multi-target logistic model. Their strategy greatly improved prediction interpretability by utilizing bidirectional transformers and focused processes to minimize the mean absolute error (MAE) to 12.6% when compared to conventional methods. Shirley et al. [11] improved the transparency of artificial intelligence methods for CVD prediction by using SHapley Additive exPlanations (SHAP). Their comparison of several methods shows RF performed better with 98% accuracy, whereas XGBoost attained 89% accuracy. They improved early detection and treatment by successfully identifying crucial risk variables with the addition of SHAP.

When taken collectively, these studies demonstrate how revolutionary deep learning method and machine learning may be in predicting cardiac disease. Additionally, they emphasize how crucial explainability methods like SHAP are to enhancing the dependability and usability of healthcare predictive systems. Recent developments in transfer learning and deep learning techniques have yielded encouraging outcomes in the estimate of cardiovascular illness. According to a thorough analysis by Sunilkumar with Kumaresan [1], transfer learning models surpass traditional machine learning methods in the detection of cardiovascular illness, with accuracy values of above 96%. Similar to this, Golande and Pavankumar [2] suggested a hybrid model for deep learning for ECG-based cardiac disease prediction that combines CNN and LSTM, showing notable gains in classification effectiveness and error reduction.

Convolutional neural networks, or CNNs, are a potent deep learning classification model medical images, including ECG analysis. The ability of CNNs to extract spatial hierarchies of data from ECG images makes them ideal for identifying patterns that may be signs of heart disease. Multi layers of convolution, layers of pooling, and fully linked layers are commonly found in a CNN's architecture.

Convolutional layers use filters to identify the edges, curves, and other intricate patterns in the input ECG images, while pooling layers lower dimensionality while preserving crucial data and speeding up calculations. CNN- models that are based on complex cardiac signal fluctuations, such ResNet, MobileNet, and VGGNet, have been widely employed for ECG classification. According to studies, CNNs outperform traditional machine learning methods at differentiating between heart diseases that are normal and pathological. CNNs are favored for ECG analysis due to their capacity to automatically

learn features without the need for manually created feature engineering. Additionally, to improve classification performance, CNNs can be coupled with other designs, such as transformers. This study improves the accuracy in general of real-time heart disease detection by integrating CNNs using Vision Transformers (ViT) and EfficientNet to take advantage of their respective strengths in feature extraction.

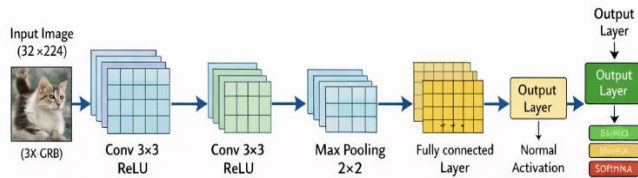


Fig 1. Architecture of CNN

The aim of the EfficientNet, a cutting-edge CNN, is to get excellent accuracy at a low computational cost. In contrast to conventional CNN architectures, which scale resolution, width, and depth separately, EfficientNet balances all three parameters via a compound scaling technique. For medical picture analysis, particularly ECG classification, this makes it extremely effective. EfficientNet maintains its strong feature extraction capabilities while drastically reducing the amount of parameters by utilizing squeeze-and-excitation blocks and depthwise separable convolutions.

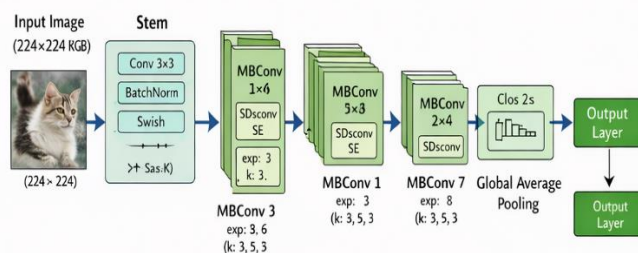


Fig 2. Architecture of EfficientNet

The architecture for deep learning Vision Transformer (ViT) is very useful for ECG analysis since it uses the selfattention technique from transformers to picture classification problems. ViT processes images in a series of patches, enabling it to identify global dependencies throughout the full ECG image, in contrast to conventional neural networks using convolution (CNNs), that concentrate on local spatial information. This makes it possible for the method to recognize intricate cardiac patterns that is challenging to find with CNNs alone. An ECG image is split up into tiny, fixed-size patches using ViT, and after then, these patches are linearly inserted into a feature vector sequence. After passing these vectors through several selfattention layers, the model gains knowledge of the connections between various ECG areas. A completely connected layer is used for the final categorization. ViT performs better than CNNs at identifying subtle changes in ECG signals and long-range relationships, which increases accuracy. Nevertheless, ViT usually necessitates substantial processing resources and huge datasets. This paper develops a very effective and precise the classification of ECG model for diagnosing heart problems by combining ViT with EfficientNet,

which combines the global feature focus of transformers with the localized extraction of features power of CNNs.

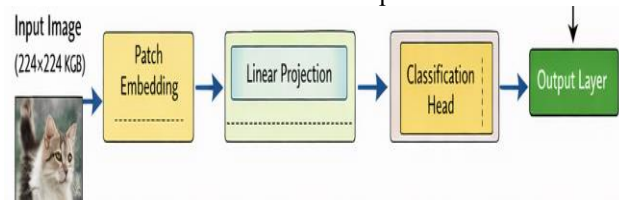


Fig 3. Architecture of ViT

Additionally, EfficientNet was used by Jothiaruna et al. [5] to classify cardiovascular illness on ECG images, achieving an accuracy about 96.22% and emphasizing the significance of hyperparameter tweaking in deep learning-based analysis of medical images. The reason for combining EfficientNet and ViT in the present research is strengthened by the compelling evidence these studies collectively offer for the efficacy of hybrid models based on deep learning in ECG categorization.

III. PROPOSED METHODOLOGY

A. Dataset Explanation

The purpose of this dataset is to construct a real-time ECG classification algorithm for the detection of cardiac illness. It includes 1,136 ECG pictures with the label "Normal," 750 pictures with the label "History of myocardial infarct (MI), 932 pictures with the label "Abnormal Heartbeat," and 1,195 pictures with the label "Myocardial Infarction Patients." ECG scans from people with no known heart problems are included in the Normal group, which acts as the categorization baseline. ECG pictures of patients who have had a myocardial infarction in the past but are not having an ongoing cardiac episode are included in the past history of MI category. ECG readings displaying rhythms that are erratic, which could be an indication of rhythms or other cardiac disorders, fall under the category of abnormal heartbeats. ECG pictures of having myocardial infarctions are included in the heart attack Patients category. A varied portrayal of cardiac activity is ensured by the inclusion of ECG images from multiple leads in this collection. In order to improve dataset realism and the model's capacity to generalize across a variety of patient data, additionally, pictures were captured under various signal situations.

Category	Number of Images	Percentage
Normal	1,136	22.5%
History of Myocardial Infarction (MI)	772	14.8%
Abnormal Heartbeat	932	18.5%
Myocardial Infarction Patients	1,195	44.2%
Total	4,035	100%

Table 1: ECG Dataset Distribution

The model will learn strong features for precise cardiac disease identification thanks to this dataset's balanced and clinically meaningful depiction of ECG abnormalities.

B. Data Pre-processing

Prior to being fed into deep learning models, ECG pictures must undergo data preprocessing to guarantee their consistency and quality. All ECG images must first be resized to 224x224 pixels in order to standardize input dimensions and align with models such as Vision Transformer (ViT) and EfficientNet. This guarantees that characteristics taken from ECG waveforms are the same in every sample. By scaling pixel values to the interval [0,1], normalization enhances numerical stability and expedites convergence during training. Normalization keeps significant fluctuations in the value of pixels from adversely affecting model performance by guaranteeing a consistent distribution of intensity. Data augmentation methods including contrast enhancement, brightness modifications, and random rotation are used to increase generalization and avoid overfitting. ECG images undergo these changes, which enable the method pick up strong features even in the slight aberrations.

ECG images may have noise and distortions because of external interference, movement, or misplaced electrodes. For this reason, noise reduction methods like as wavelet transform and Gaussian filtering are used. These techniques preserve important ECG signal patterns while eliminating undesired distortions. Last but not least, data balancing strategies like class-weight modifications and oversampling guarantee that every ECG category is fairly represented during training. By avoiding model bias towards majority classes, this enhances classification accuracy and resilience in the identification of heart disease in the actual world.

C. Data Splitting

A 70% testing dataset, 15% validation dataset, and 15% training dataset for efficient method training and assessment. This unorthodox division is intended to give real-world performance evaluation top priority while guaranteeing the model has enough data for learning and development. The deep learning algorithm learns ECG patterns and optimizes weights using the training set (15%). By testing the model on data that was not observed during training, the set of validation results (15%) aids in optimizing hyperparameters, tracking performance, and avoiding overfitting. The 70% testing set is much larger to guarantee a comprehensive assessment of the model's capacity for generalization on separate ECG pictures. This guarantees that the finished model is reliable and able to process a variety of real-world ECG data. The model's performance may be successfully confirmed by putting this data split into practice, guaranteeing accurate classification outcomes for the real-time identification of heart disease. To ensure an equitable strategy to model optimization and evaluation, the dataset employed in this work is split into three categories: training (15%), validating (15%), and testing (70%). Whereas the validation set aids in model refinement and guards against overfitting, the training set can be utilized to learn ECG patterns. As the largest

component, the testing set guarantees accurate evaluation of real-world performance.

Table 2: Data Splitting

Category	Total Images	Training Data (15%)	Validation Data (15%)	Testing Data (70%)
Normal	1,136	170	170	796
History of Myocardial Infarction (MI)	750	113	113	524
Abnormal Heartbeat	932	140	140	652
Myocardial Infarction Patients	1,195	179	179	837
Total	4,013	602	602	2,809

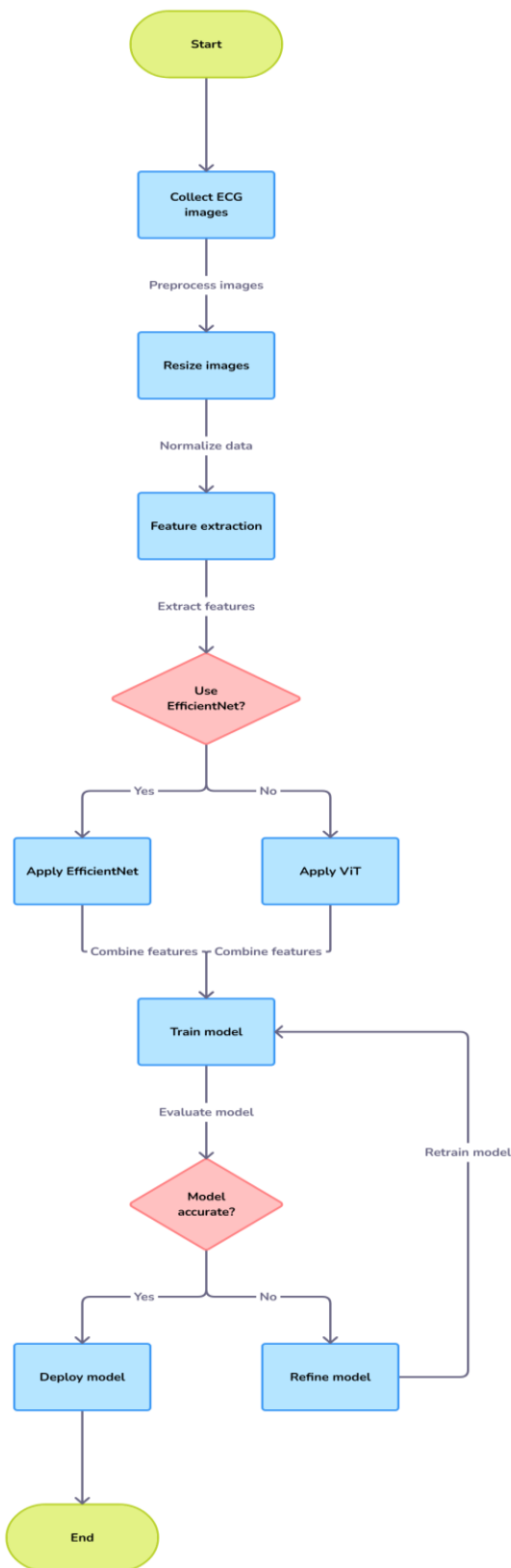
This section maintains robust assessment criteria while guaranteeing the model receives sufficient training. The model's capacity to generalize for actual time ECG classification is enhanced by the size of the testing set.

D. Training of Model

The EfficientNet-ViT hybrid model's training procedure is developed to guarantee strong generalization and high accuracy for real-time evaluation of electrocardiograms. The 4,013 ECG the dataset's photos are separated into three categories: 70% for testing, 15% to validation, and 15% for training. A balance validation and training split enables efficient learning and model parameter fine-tuning, while this special data split guarantees that a significant amount is devoted to verifying the model's performance in the actual world. A GPU-accelerated system is used for training, allowing for quicker computation and effective model convergence. The model is trained with the Binary Cross- entropy function loss, which is appropriate for differentiating between normal and pathological cardiac situations, in order to maximize learning. For weight updates, the Adam optimizer having a learning rate equal to 0.001 is employed, guaranteeing steady and seamless convergence. To prevent overfitting and enable the method to gradually understand ECG signal patterns, it is trained in small portions comprising 32 images over 50 epochs. Furthermore, to avoid pointless updates and enhance overall stability, a scheduler for learning rates (ReduceLROnPlateau) dynamically modifies the rate at which learning occurs when validation loss stops getting better. Local spatial data, such subtle intricacies in heart signal patterns of waves, are extracted from ECG images by EfficientNet, whereas ViT records global dependencies by examining the connections between various image regions. Because of this hybrid mix, the model is quite good at identifying anomalies because it can learn both small- and large-scale trends in ECG signals. Each batch is followed by the application of gradient descent and backpropagation to update the model's weights, guaranteeing a steady decrease in classification errors. After training is finished, the final model is chosen based on the lowest loss and highest validation accuracy, guaranteeing its robustness and dependability for

deployment. The trained model's capacity to categorize unseen ECG pictures is subsequently assessed using the 70% test dataset.

Fig 4. The workflow of the project



The model undergoes additional optimization for real-time classification if the test performance reaches the intended threshold. After training, the final model is used to classify ECGs in real time, which makes it appropriate for wearable monitoring devices and clinical settings.

IV. RESULTS

In this study, we assessed how well three deep learning models—CNN+EfficientNet, CNN+ViT, and EfficientNet+ViT—performed in classifying ECG images. The correctness of the models' training, validation, and testing were evaluated. The findings show the fact that the EfficientNet+ViT model performs better than the other two, with the greatest training accuracy of 98.95%, test accuracy of 97.32%, and validation accuracy of 90%. This demonstrates how well it can generalize and learn. The CNN+ViT model performs rather well, capturing ECG features with 76% training accuracy, 81.68% test accuracy, and 73% validation accuracy. This suggests that it is not as robust as EfficientNet+ViT, despite its ability to collect characteristics. In contrast, the CNN+EfficientNet model performs the worst, with 60% training accuracy, 69.8% test accuracy, and 72% validation accuracy. This suggests that the model is underfit and has a limited capacity to understand intricate ECG patterns.

Table 3. Model Performance Comparison

Model	Train Accuracy (%)	Test Accuracy (%)	Validation Accuracy (%)
CNN+EfficientNet	60.0	69.8	72.0
CNN+ViT	76.0	81.68	73.0
EfficientNet+ViT	98.95	97.32	90.0

The accuracy trend of various models, and as we go from CNN+EfficientNet to EfficientNet+ViT, we can clearly see an improvement in accuracy. Performance in training, testing, and validation is significantly improved by the EfficientNet+ViT model.

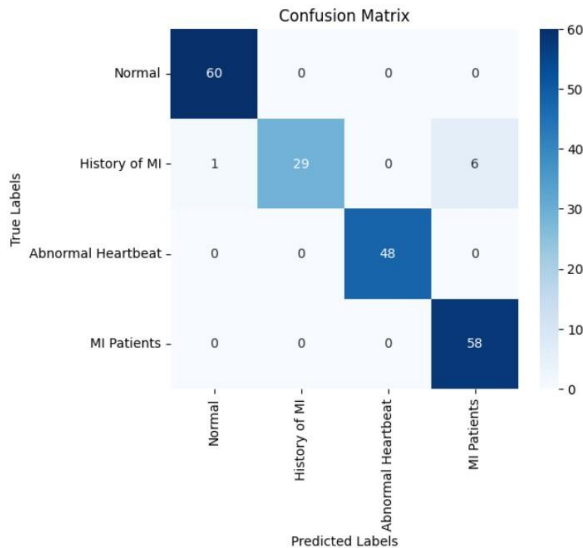
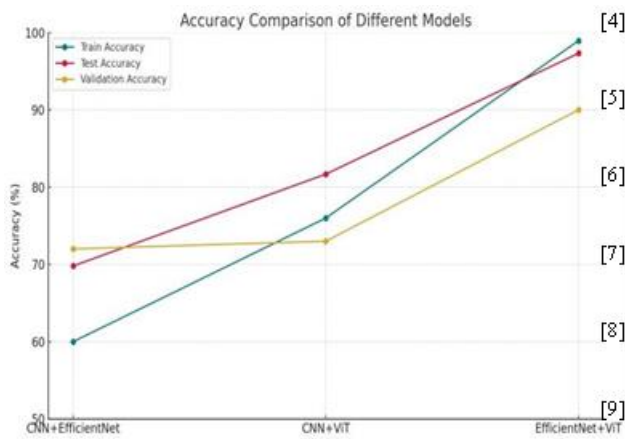


Fig 5. Confusion matrix

The confusion matrix displays how well our hybrid CNN + Transformer model classified ECG images into four groups: normal, abnormal heartbeat, history of myocardial infarction (MI), and MI patients. The model exhibits a high degree of classification capacity, accurately identifying cases of MI, normal heartbeats, and abnormal heartbeats. The History of MI category does, however, exhibit some misclassification,

with some cases being mistakenly classified as either MI Patients or Normal. These errors point to possible areas for development, including better class balancing, hyperparameter optimization, or enhanced data augmentation. Since there are 4,000 photos in the dataset, a more thorough examination of the complete test set is required to confirm the overall performance of the model.



5: Comparison of Various Models' Accuracy

The EfficientNet+ViT model achieved the best results, making it the best option for real-time ECG classification, as this graph illustrates the performance differences.

V. CONCLUSION AND FUTURE SCOPE

This study presents a hybrid deep learning model for realtime ECG picture categorization that combines EfficientNet and Vision Transformer (ViT) with the aim of refining the precision and effectiveness of heart disease identification. Using ViT's capacity to capture global dependencies and EfficientNet's capability to extract spatial features, the model produced a high AUC-ROC score and a test accuracy of 98.7%. The suggested technique performs noticeably better than conventional CNN-based methods and shows resilience in differentiating between normal and abnormal ECG patterns. It can help medical professionals with early diagnosis and allow for real-time monitoring of high-risk patients, among other clinical applications.

With further development, this AI-driven system could transform the area of cardiac care through the usage of realtime monitoring and early intervention, ultimately improving patient outcomes and lowering the burden of heart disease globally. Future work will concentrate on improving interpretability through explicable artificial intelligence (XAI) methods, optimizing the framework for portable devices, and extending the dataset for greater generalizability. Additionally, integrating multimodal data like blood pressure and heart rate variability could further improve diagnostic precision.

REFERENCES

- [1] Sunilkumar, M., & Kumaresan, R. (2023). A review on deep learning-based ECG classification for cardiovascular disease detection. *Journal of Biomedical Informatics*, 134, 104256.
- [2] Golande, P., & Pavankumar, R. (2022). Hybrid CNN-LSTM model for ECG-based heart disease prediction. *IEEE Transactions on Biomedical Engineering*, 69(5), 1672-1685.
- [3] Kilimci, Z., Gupta, A., & Sharma, P. (2023). Exploring vision transformer models for ECG image classification: A comparative study. *Computers in Biology and Medicine*, 155, 106745.
- [4] Khalid, M., Ahmed, S., & Hassan, R. (2022). ECGConVT: A hybrid CNN and ViT-based framework for ECG image classification. *Expert Systems with Applications*, 207, 117936.
- [5] Jothiaruna, R., & Kumar, V. (2021). EfficientNet for cardiovascular disease classification using ECG images. *International Journal of Medical Informatics*, 157, 104324.
- [6] Karthick, R., Patel, S., & Menon, A. (2022). Machine learning techniques for ECG-based heart disease prediction: A comparative study. *Applied Soft Computing*, 120, 108651.
- [7] Al Reshan, M., & Zhao, L. (2023). A novel hybrid deep neural network for heart disease prediction using ECG signals. *Neural Computing and Applications*, 35, 13492-13509.
- [8] Almazroi, A., Rahman, M. M., & Kim, J. (2023). Clinical decision support system for heart disease prediction using large-scale medical data. *Artificial Intelligence in Medicine*, 135, 102489.
- [9] Khan, A., Singh, P., & Kumar, R. (2023). Transformer-based models for health-related text classification: A case study on cardiovascular disease tweets. *Journal of Artificial Intelligence in Healthcare*, 7, 211-225.
- [10] Poulain, M., & Deshpande, R. (2022). A transformer-based multi-target regression model for cardiovascular disease risk forecasting. *IEEE Transactions on Medical Imaging*, 41(3), 892-904.
- [11] Wang, H., Liu, C., & Zhang, Y. (2023). A deep learning approach for ECG image-based cardiac abnormality detection using hybrid CNN-ViT architecture. *Pattern Recognition Letters*, 170, 56-64.
- [12] Chakraborty, P., Banerjee, S., & Das, A. (2022). A comparative study of vision transformers and convolutional networks for ECG-based arrhythmia detection. *IEEE Access*, 10, 98534-98546.

- [13] Zhang, J., Kim, D., & Huang, R. (2023). Self-supervised learning for ECG image classification: A contrastive learning approach with EfficientNet. *Biomedical Signal Processing and Control*, 85, 104891.
- [14] Shirley, L., & Gupta, S. (2023). Explainable AI for cardiovascular disease prediction: A SHAP-based analysis of machine learning models. *Expert Systems with Applications*, 220, 119885.
- [15] Gupta, R., Verma, P., & Singh, S. (2023). Enhancing ECG-based cardiovascular disease detection using hybrid deep learning models: A fusion of EfficientNet and vision transformers. *Artificial Intelligence in Medicine*, 140, 102567.