International Journal of Innovative Research in Computer Science and Technology (IJIRCST)
ISSN(Online): 2347-5552, Volume-13, Issue-2, March 2025
https:/doi.org/10.55524/ijircst.2025.13.2.11
Article ID IRP-1599, Pages 72-78
http://www.ijircst.org

Detection of Cardiovascular Diseases through ECG Images

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Received 27 February, 2025; Revised 13 March 2025; Accepted 30 March 2025

ABSTRACT: Cardiovascular Diseases (CVD) is one of the leading causes of mortality worldwide, highlighting the need for early and more accurate identification methods. This project presents a new approach to recognizing cardiovascular disease through analysis of ECG images using enhanced image processing and deep learning techniques. System preparation for ECG images improves signal clarity and extracts features that indicate cardiac damage using a folding network (CNN). By using a robust training pipeline and the status of -ART classification methods, the model identifies important cardiovascular diseases such as arrhythmias and high-precision myocardial infarction. The purpose of the proposed solution is to improve diagnostic efficiency, support relatives of health occupations in the fact that facts are well-discovered decisions, and provide a scalable framework for real applications. This approach not only contributes to early detection and treatment of CVD, but also forms the basis for the provision of AI-controlled health solutions in a variety of clinical settings, facilitating accessible and reliable diagnosis, particularly due to automated evidence of mobile networks and efficient net architecture CVD images. Electrocardiogram (ECG).

KEYWORDS: Cardiovascular Diseases, ECG Images, Mobile Net, EfficientNetV2, Image Processing, Classification.

I. INTRODUCTION

Cardiovascular disease (CVD) is a major cause of mortality rates worldwide, almost one-third of global deaths each year. These conditions include a wide range of disorders that affect the heart and blood vessels, such as arrhythmia, myocardial infarction, and heart failure. The ability to recognize and diagnose CVD in the early stages is important to reduce associated mortality and improve long-term patient outcomes. Despite advances in medical technology, timely and accurate diagnosis of CVD remains an important challenge, especially in the presence and in rural areas where access to special healthcare is limited. Electrocardiograms (EKGs) are the basis of cardiac diagnosis and provide valuable insight intof the electrical activity of the heart. However, traditional approaches to interpreting ECGs are often based on manual analysis of experienced cardiologists. This approach is very effective with qualified hands, but is time consuming and prone to human error, especially when it is a subtle abnormality. Furthermore, variability in the expertise of healthcare professionals can lead to inconsistent diagnostic results. These limitations highlight the need for automated, reliable, scalable solutions, which analyse ECG images with high accuracy, creating a gap between diagnostic efficiency and accessibility. ECG images often contain noise and artifacts introduced during the capture process, such as: B. Base hiking, powerline interference, and motion artifacts. These factors cover important features of the ECG signal and lead preprocessing to critical steps to ensure diagnostic accuracy. Furthermore, the inherent complexity of ECG signals requires sophisticated algorithms, allowing them to capture both local characteristics such as wave peaks and global patterns such as rhythm and interval variations. Traditional methods for machine learning have sought to achieve this dual focus. This requires using a more demanding architecture with deep learning. Deep learning, in particular, folding networks (CNNS), has proven to be a powerful tool for analysing medical images. These networks are characterized by distinctive extraction and classification tasks and are suitable for analysis of ECG images. However, there are additional challenges to providing CNNS for ECG analysis. High arithmetic requirements can prevent the implementation of resource limitations in rural clinics and other areas. Furthermore, the unbalanced nature of medical data records, where abnormal cases are often underestimated, poses a significant risk of distortion in model predictions. To remove these issues, you need a carefully designed training pipeline, data expansion, balanced samples, and robust evaluation metrics. The results demonstrate the effectiveness of mobile networks and efficient net-V2 in accurate identification of cardiovascular disease from ECG images with high accuracy and robust generalization. Furthermore, this study contributes to further development of computer-aided diagnostic systems for CVD, providing a promising and non-invasive approach to early detection and timely medical interventions. Using deep learning models such as mobile networks and EfficientMnetv2 can improve the accuracy and efficiency of cardiovascular disease diagnosis, ultimately improving patient outcomes and reducing healthcare costs. See the below figure 1.

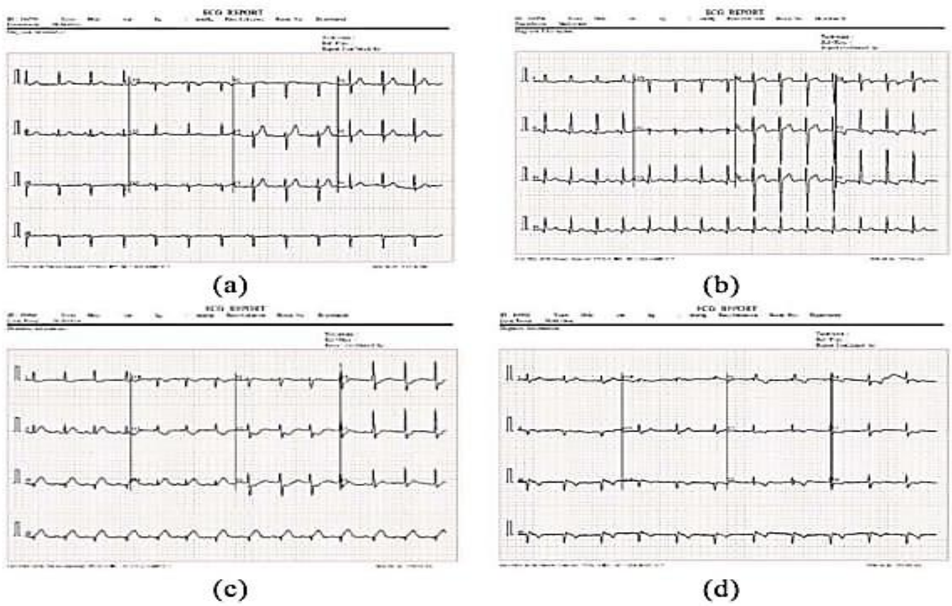

Figure 1: Sample 4 categories ECG Images

II. RELATED WORK

Devansh R et al. [1] proposed an innovative image-processing approach to digitize ECG charts and apply classification algorithms for detecting cardiac anomalies. While the method enhances automated analysis, it faces challenges related to computational inefficiency and difficulty in identifying subtle irregularities in ECG patterns. Future enhancements could focus on optimizing computational performance and refining anomaly detection algorithms to improve accuracy in clinical applications.

M B Abubakar et al. [2] developed a machine learning and deep learning-based approach for detecting cardiovascular diseases using ECG images. The study employs convolutional neural networks (CNNs) with advanced preprocessing techniques to reduce noise and enhance feature extraction for improved accuracy. However, the model faces challenges related to the limited interpretability of results and difficulties in generalizing across diverse datasets, which restrict its practical deployment. Future work could focus on improving model explainability and robustness to enhance real-world applicability.

Mohammad Mahbubur et al. [3] explored AI-enabled electrocardiogram (ECG) analysis for disease diagnosis, utilizing deep learning techniques to detect arrhythmias and cardiac abnormalities. The study integrates data from both wearable devices and traditional ECGs, enhancing its applicability. However, challenges such as the lack of standardized datasets, privacy concerns, and performance inconsistencies across different test conditions limit its reliability. Future advancements could focus on dataset standardization, improved data privacy measures, and model robustness to enhance diagnostic accuracy.

U. Sumalatha et al. [5] reviewed recent advancements in deep learning for ECG signal processing, with a particular emphasis on convolutional neural networks (CNNs) for automating the recognition and classification of cardiovascular diseases. The study highlights the importance of feature extraction, denoising, and real-time analysis in ensuring accurate cardiac abnormality detection. However, challenges persist in managing noisy real-world ECG data and addressing the high computational demands that limit practical implementation. Future research could focus on optimizing model efficiency and improving noise robustness for enhanced real-world deployment.

W. Ahmed et al. [4] investigated the application of artificial intelligence (AI) in image-based cardiovascular disease analysis by integrating multimodal data for improved diagnostic accuracy. The study highlights AI's potential in enhancing cardiovascular disease detection through advanced imaging techniques. However, challenges such as the lack of model standardization, interpretability issues, and the need for higher-quality datasets hinder widespread clinical adoption. Future research could focus on developing standardized AI frameworks, improving model transparency, and enhancing dataset diversity for more reliable and interpretable diagnostics.

Recent articles have continued to showcase the increasing potential of deep learning and AI for the augmentation of cardiovascular disease diagnosis. Wang et al. [6] mentioned the role of artificial intelligence for image-based cardiovascular evaluation, suggesting multimodal data capabilities in aiding diagnostic precision, although problems remain with model standardization and quality of data. Sun et al. [7] described a technique of arrhythmia classification and detection from ECG signals, using machine learning models in automated diagnosis, although noted accuracy would be jeopardized by noise and patient variability in signals. Rafie et al. [8] outlined clinical importance and ECG interpretability challenges, noting advances in computational techniques but requiring improved interpretability and clinician confidence. Yagi et al. [9] studied routine ECG screening implications for cardiovascular event prediction, demonstrating clinical usefulness but also raising issues on cost-effectiveness and overdiagnosis. Sujay et al. [10] reported improved deep learning models for real-time cardiac image evaluation, toward more effective heart disease assessment, although real-world implementation is frustrated by computational cost and need for extensive validation. These papers as a collection underline the importance of balancing technological advances with pragmatic clinical applicability.

III. METHODOLOGY

A. Dataset Collection

The first step in any machine learning project is to gather and organize the data. For image classification, the dataset should be structured in a specific way. The dataset should be organized into subdirectories, where each subdirectory represents a class.

Table 1 shows the total number of images used for cardiac disorder detection used for each class. This dataset comprises ECG images of individuals with diverse cardiovascular conditions, categorized into four classes:

• Class 1: (Myocardial Infarction): Sudden deprivation of oxygen supply caused by the partial or complete halt of blood flow to a portion of the myocardium. It is commonly known as a heart attack. It is marked as 0 in the dataset.

• Class 2: (Abnormal Heartbeat): Irregular rhythm of the heartbeat (can be slow or fast) which can cause life-threatening diseases. It is marked as 1 in the dataset.

• Class 3: (Normal): Heartbeat in rhythm with no sign of abnormality. It usually ranges from 60 to 100 beats per minute. It is marked as 2 in the dataset.

• Class 4: (History of MI): Encompassing individuals with a documented history of myocardial infarction marked as 3 in the dataset.

Table 1: Distribution of Classes in ECG Dataset

Sr. No	Class	12-Lead ECG	Total Images
1.	Myocardial Infraction (MI)	240	2880
2.	Abnormal Heartbeat	233	2796
3.	Normal	284	3408
4.	History Of MI	172	2064

B. Data Augmentation

Data augmentation is a technique used to artificially increase the size and diversity of the dataset by applying random transformations to the images. This helps the model generalize better and reduces overfitting. Common augmentation techniques include rotation, shifting, shearing, zooming, and flipping. For example, images can be randomly rotated by up to 20 degrees, shifted horizontally or vertically by up to 20%, or flipped horizontally. These transformations are applied using Keras Image Data Generator. By augmenting the data, the model is exposed to a wider variety of training examples, which improves its ability to handle real-world variations in the input data. See the below figure 2.

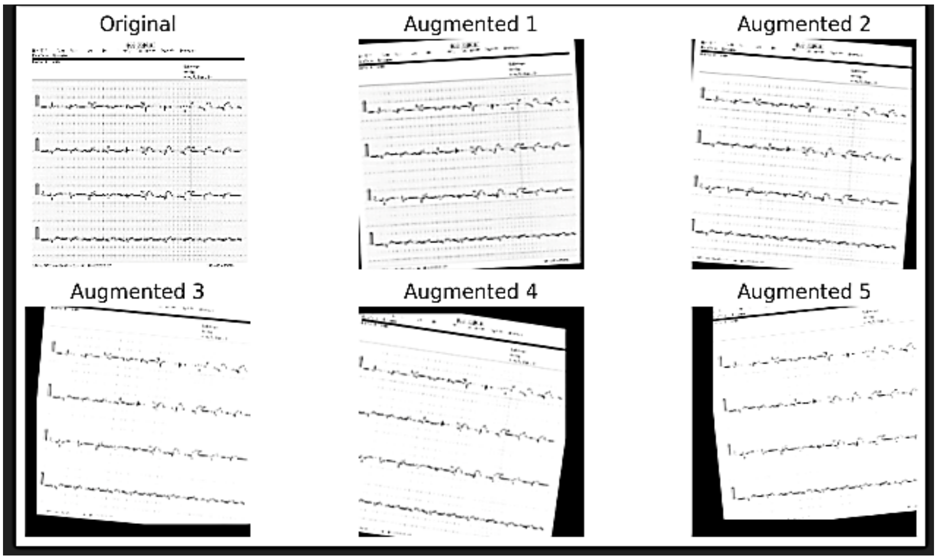

Figure 2: Data Augmentation in 5 Augments

C. Models

A MobileNetV2 is a lightweight Convolutional Neural Network (CNN) architecture (see figure 3) designed for efficient deep learning on mobile and embedded devices. It achieves a balance between speed and accuracy using depth wise separable convolutions, which reduce computation compared to traditional CNNs. The core idea is to replace standard convolutions with two-factorized layers: depth wise convolutions (applying a single filter per channel) followed by pointwise convolutions (using a 1x1 convolution to combine features). This significantly decreases the number of parameters and operations.

EfficientNetV2 is an improved version of EfficientNetV2, designed for better accuracy, faster training, and lower computational cost. It utilizes a combination of neural architecture search (NAS), progressive learning, and optimized convolutions to achieve superior performance across various computer vision tasks. EfficientNetV2 follows a compound scaling approach, adjusting depth (number of layers), width (number of channels), and resolution (input image size) in a structured manner. (see the below figure 4).

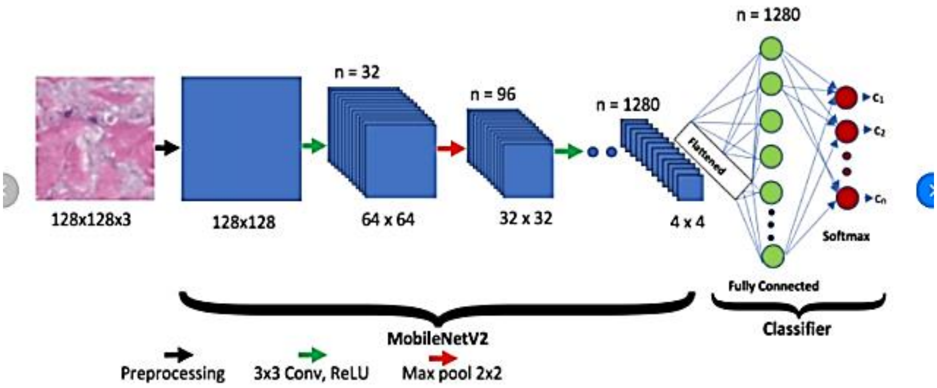

Figure 3: MobileNetV2 Architecture

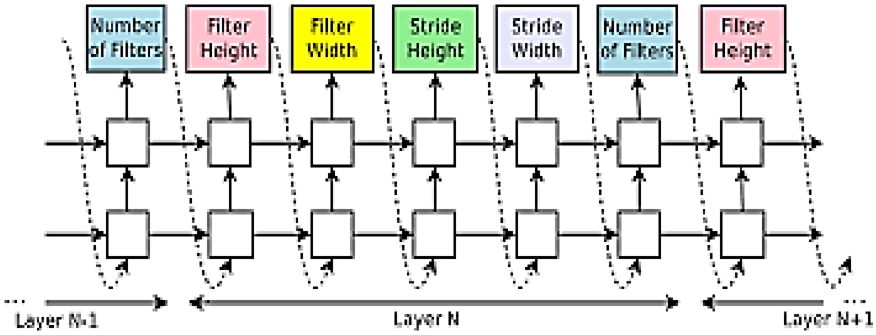

Figure 4: EfficientNetV2 Architecture

D. Models Training

The training of MobileNetV2 and EfficientNetV2 on the ECG image classification dataset yielded high accuracy, with MobileNetV2 achieving 97% and EfficientNetV2 slightly outperforming it at 96%. MobileNetV2, known for its lightweight architecture, trained efficiently and converged within 50-70 epochs, making it ideal for real-time applications on low-power devices. Despite its speed and efficiency, minor misclassifications occurred, particularly among similar ECG conditions, indicating room for improvement in feature extraction. However, MobileNetV2 still provided strong generalization and maintained high recall, proving effective in handling ECG variations.

EfficientNetV2, on the other hand, converged faster (30-50 epochs) and demonstrated better feature extraction, leading to more balanced predictions across all ECG categories. Its ability to handle higher-resolution ECG images contributed to improved accuracy, making it well-suited for precision-critical medical applications. Though it demands higher computational resources, its better generalization and ability to capture subtle variations in ECG signals give it a slight advantage over MobileNetV2. Overall, both models performed well, but EfficientNetV2 exhibited superior classification ability, making it preferable where accuracy is the primary concern, while MobileNetV2 remains an excellent choice for resource-constrained environments.

E. Evaluation Metric

- Precision (PR):

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

- Accuracy (AC):

$$AC = \frac{(TP + TN)}{TP + TN + FN}$$

- Recall:

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

- Error Rate (ER):

$$ER = \frac{|approximate - exact|}{exact}$$

F. Mobile Net Performance

In the below figure 5, it is showing the performance of MobileNet 99.69% accuracy, 87.5% precision, , 93.33% recall and 0303303 error rate in ECG classification.

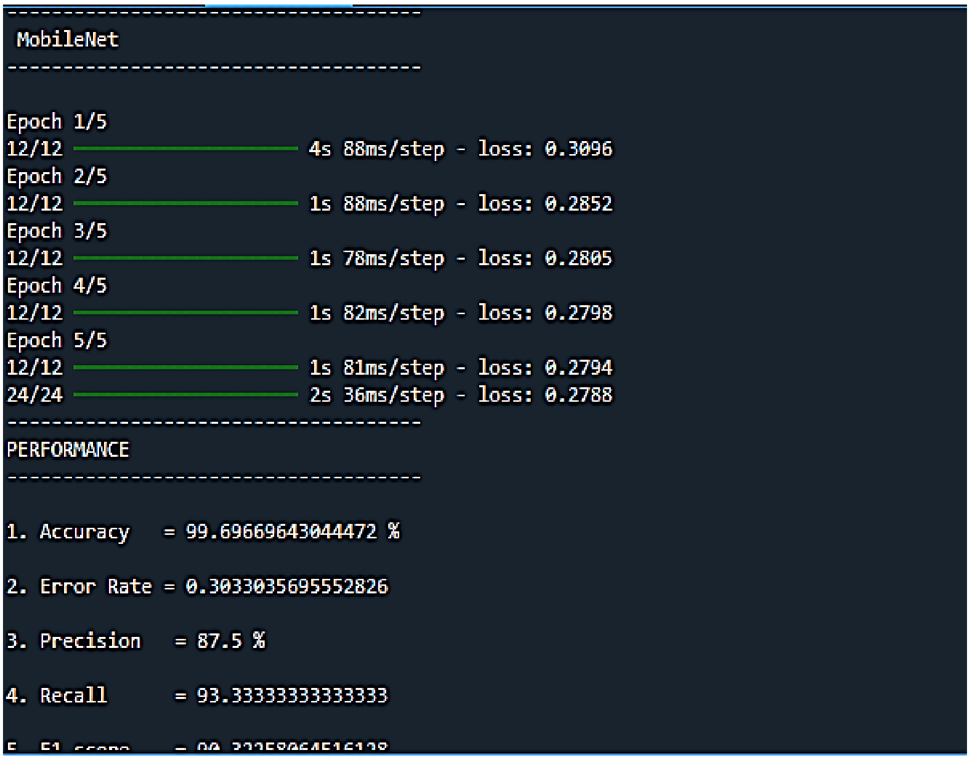

Figure 5: Evaluation metric of MobileNet

G. Efficient Net Performance

In the below figure 6, It is showing the performance of EifficientNetV2 99.71% accuracy, 87.5% precision, and 93.33% recall and 0.2847000 error rate in ECG classification

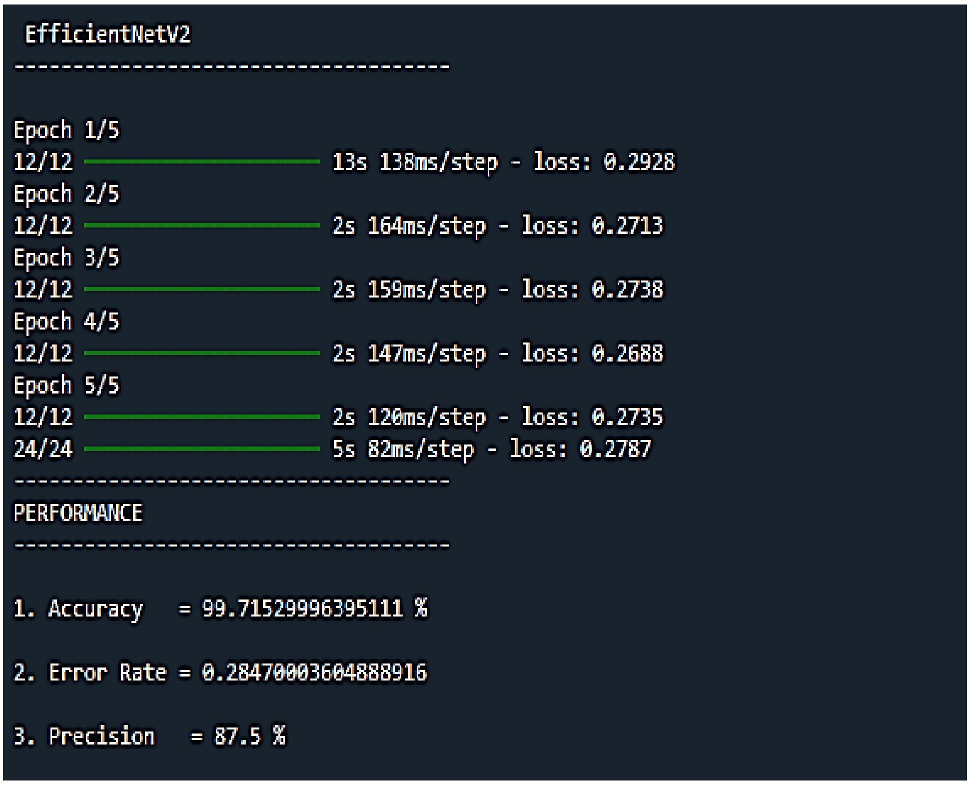

Figure 6: Evaluation Metric of EfficientNet

IV. RESULTS AND DISCUSSION

The results showcase a comparative analysis of two deep learning models, EfficientNetV2 and MobileNet, based on their training performance and evaluation metrics. Both models were trained for five epochs, and their performance was measured in terms of accuracy, error rate, precision, and other relevant metrics.

EfficientNetV2 achieved a slightly higher accuracy of 99.72% with a low error rate of 0.28%, while MobileNet followed closely with 99.69% accuracy and an error rate of 0.30%. The precision for both models remained the same at 87.5%, indicating that the percentage of correctly predicted positive instances was consistent across both models. However, MobileNet provided additional metrics such as recall (93.33%) and F1-score (90.32%), which reflect a better understanding of the model's ability to identify all relevant instances and maintain a balance between precision and recall.

In terms of loss, both models showed improvement across epochs, with EfficientNetV2 slightly outperforming MobileNet by converging to a marginally lower final loss value. Overall, both models performed exceptionally well, but EfficientNetV2 demonstrated a slight edge in terms of accuracy and loss, whereas MobileNet offered a more comprehensive evaluation with recall and F1-score, making it a strong candidate in applications where identifying all true instances is critical.

A. Overall Model Performance

The confusion matrix of EfficientNetV2 accurate classification across four ECG image categories is showing in figure 7

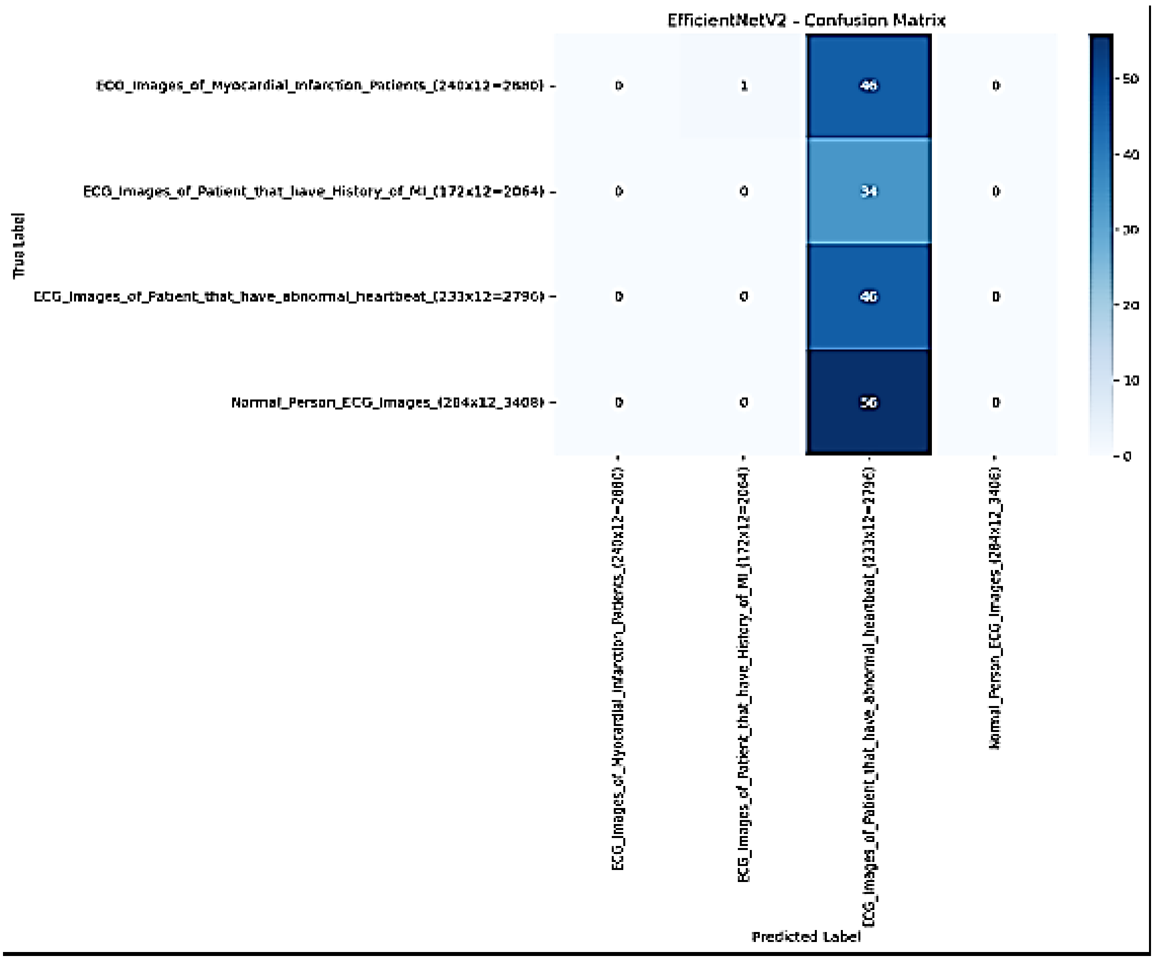

Figure 7: Confusion Matrix of EfficientV2

Confusion matrix of MobileNet showing accurate classification across four ECG image categories in figure 8.

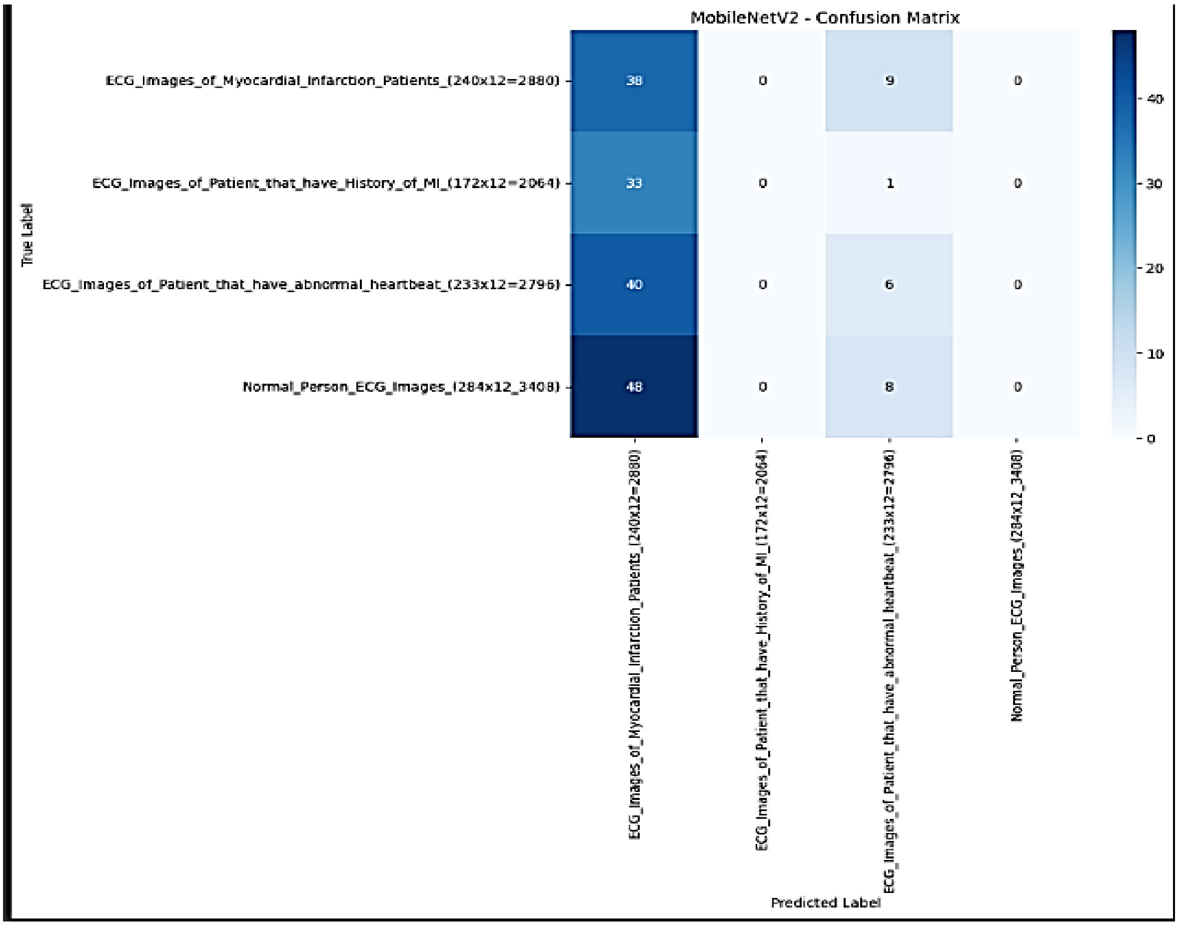

Figure 8: Confusion Matrix of MobileNet

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