Feature Extraction and Fusion of ECG Signals Using MFCC and DWT for Cardiovascular Disease Diagnosis

Mr Vaibhav Vasudevarao Gijare[1], Dr Sushant Kumar[2]
[1]Research Scholar- PhD, Department of Electronics and Communication Engineering,
Indian Institute of Information Technology, Pune
Assistant Professor, MIT Academy of Engineering, Alandi(D), Pune.
vaibhavgijare21@ece.iiitp.ac.in
[2]Assistant Professor, Department of Electronics and Communication Engineering
Indian Institute of Information Technology, Pune
sushant@iiitp.ac.in

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ABSTRACT

Cardiovascular diseases (CVDs) remain a leading cause of mortality globally, making early and accurate detection crucial for effective treatment. Electrocardiogram (ECG) signals play a vital role in diagnosing these conditions, and advanced feature extraction and classification techniques can enhance detection accuracy. The objective of this research is to develop and implement feature extraction and classification methods for ECG signals using lightweight deep learning models, tailored for real-time CVD detection on IoT devices. The proposed method integrates Mel Frequency Cepstral Coefficients (MFCC) and Discrete Wavelet Transform (DWT) to extract significant features from ECG signals, capturing both frequency-domain and time-domain information. By combining these complementary features, the method enhances the ability to identify patterns indicative of cardiovascular diseases. For classification, Convolutional Neural Networks (CNNs) and two lightweight deep learning models, VGG16 and MobileNet, are employed to ensure computational efficiency while maintaining high accuracy. The lightweight nature of these models makes them suitable for deployment on resource-constrained IoT devices, enabling real-time monitoring. The models are validated using real-world datasets to ensure robust performance, with sensitivity and specificity as key metrics for evaluating their effectiveness in detecting CVDs. The results demonstrate that the proposed feature extraction and fusion method, coupled with optimized lightweight models, achieves high accuracy in classifying ECG signals, contributing to early detection and intervention of cardiovascular diseases. The research shows promising potential for real-time, on-device implementation in healthcare systems, offering an efficient, scalable solution for CVD detection.

1. INTRODUCTION

Cardiovascular diseases (CVDs) have long been recognized as one of the most prevalent causes of death worldwide, accounting for approximately 17.9 million deaths annually, according to the World Health Organization (WHO). These diseases encompass a broad range of conditions, including coronary artery disease, heart failure, arrhythmias, and stroke, all of which are driven by a combination of genetic, environmental, and lifestyle factors[1]. The growing incidence of CVDs places immense pressure on healthcare systems, highlighting the need for innovative approaches to diagnosis, treatment, and prevention. Early detection of CVDs is crucial for mitigating the risk of severe complications and improving patient outcomes. However, current diagnostic methods often lack the precision and real-time capacity required for effective intervention, leading to missed opportunities in timely disease management[2], [3].

The Role of Electrocardiogram (ECG) Signals in CVD Diagnosis

The electrocardiogram (ECG) is a well-established, non-invasive tool used to record the electrical activity of the heart. It is widely regarded as one of the most essential diagnostic methods for identifying irregularities in heart function, such as arrhythmias, myocardial infarction, and other conditions associated with CVDs. ECG signals offer valuable insights into the electrical impulses that govern heart contractions, enabling clinicians to detect abnormalities in the rhythm, rate, and overall functionality of the heart. Despite the widespread use of ECG in clinical practice, the interpretation of ECG signals can be a complex and time-consuming task, particularly when faced with subtle or rare abnormalities[4], [5].

The traditional process of ECG signal analysis often relies on manual interpretation by cardiologists, which, although effective, is subject to human error and variability. Moreover, the volume of data generated by continuous ECG monitoring systems presents a challenge in terms of processing, storage, and analysis. These limitations highlight the need for automated systems that can accurately classify ECG signals and detect cardiovascular diseases in real time, particularly in environments where access to specialist care may be limited. To this end, advancements in artificial intelligence (AI) and deep learning have opened up new avenues for enhancing ECG signal analysis, paving the way for more accurate and timely CVD detection.

Challenges in Cardiovascular Disease Detection

Despite the potential of ECG-based diagnostic tools, there are several challenges that limit their effectiveness in practice. Traditional methods of analyzing ECG signals often rely on feature extraction techniques that may not fully capture the complexity of the signal, particularly in cases where multiple diseases or conditions are present. Furthermore, the performance of classification algorithms is often hindered by the variability and noise inherent in ECG signals, as well as the imbalance in datasets used for training machine learning models[6], [7].

Another significant challenge lies in the development of models that can be deployed on resource-constrained devices, such as wearable health monitors and Internet of Things (IoT) devices[8][9]. These devices are increasingly being used in remote monitoring of patients with cardiovascular conditions, enabling continuous, real-time health tracking. However, the limited computational resources available on these devices present a barrier to the implementation of complex deep learning models, necessitating the development of lightweight models that maintain high accuracy while minimizing resource consumption.

The Role of Deep Learning in Healthcare

The advent of deep learning has revolutionized various domains, including healthcare, where it has been applied to tasks ranging from medical imaging to predictive analytics. In particular, deep learning models, such as Convolutional Neural Networks (CNNs), have demonstrated remarkable success in classifying medical data, including ECG signals. These models have the ability to learn hierarchical features from raw data, capturing both local and global patterns that are indicative of disease states. This capability makes deep learning models well-suited for the analysis of complex biomedical signals, such as ECGs[10], [11].

However, deep learning models are typically computationally expensive, requiring significant memory and processing power, which limits their deployment on devices with limited resources. To address this issue, lightweight deep learning models, such as MobileNet and VGG16, have been developed. These models are specifically designed to perform efficiently on resource-constrained platforms, such as IoT devices, while maintaining high accuracy in classification tasks. The use of lightweight models in ECG signal analysis holds great promise for real-time, on-device cardiovascular disease detection.

Feature Extraction in ECG Analysis

Feature extraction is a critical step in the analysis of ECG signals, as it allows for the transformation of raw data into a more manageable and informative representation. Traditional methods of feature extraction typically involve techniques such as time-domain and frequency-domain analysis, which capture specific characteristics of the ECG signal, such as amplitude, duration, and frequency components. However, these methods may not fully capture the complex, non-linear nature of ECG signals, which can limit their effectiveness in detecting subtle abnormalities associated with cardiovascular diseases[12], [13].

To overcome these limitations, more advanced feature extraction techniques have been proposed, such as the Mel Frequency Cepstral Coefficients (MFCC) and Discrete Wavelet Transform (DWT). MFCC is widely used in audio signal processing and has been adapted for use in biomedical signal analysis due to its ability to capture essential frequency characteristics. DWT, on the other hand, provides a multi-resolution analysis of the ECG signal, allowing for the decomposition of the signal into various frequency components, thereby capturing both time-domain and frequency-domain features. By combining these two feature extraction methods, a more comprehensive representation of the ECG signal can be obtained, improving the accuracy of classification models.

Research Gaps

While deep learning models have shown promise in ECG signal classification, there remain several gaps in the current research. Firstly, many existing models are not optimized for deployment on lightweight devices, which limits their applicability in real-time, on-device cardiovascular disease detection. Also, the integration of multiple feature extraction techniques, such as MFCC and DWT, has not been widely explored in the context of ECG signal analysis, despite the potential benefits of combining time-domain and frequency-domain features.

Finally, while deep learning models have demonstrated high accuracy in controlled environments, there is a need for further validation using real-world datasets to ensure their robustness in practical applications. Addressing these research gaps is essential for the development of effective, scalable solutions for cardiovascular disease detection using ECG signals.

2. LITERATURE REVIEW

The application of deep learning and machine learning techniques to electrocardiogram (ECG) signal analysis has gained increasing attention in recent years, as CVD remain a significant global health issue. These advanced methodologies aim to improve the accuracy and efficiency of CVD detection, overcoming limitations of traditional diagnostic approaches. Several studies have explored different models and techniques for feature extraction, classification, and prediction of CVDs from ECG signals, contributing valuable insights into automated and precise diagnostics.

One approach to detecting abnormalities in heart dynamics involves the use of multifractal analysis of ECG signals, which identifies variations in heart dynamics through nonlinear features extracted from the ECG waveform. This technique allows for the detection of subtle changes in heart rhythm that may indicate the presence of cardiovascular diseases[14]. Similarly, mathematical models combined with autoregressive processes have been employed to model ECG signals, providing a robust framework for understanding the temporal characteristics of heart activity. These models are particularly useful in reducing noise and improving the clarity of the ECG signal, facilitating better classification of heart conditions[15].

In recent research, machine learning techniques have been employed to classify congenital heart defects using ECG signal analysis. This involves extracting relevant features from the ECG signals and using classification algorithms to accurately identify specific congenital defects. The use of machine learning in this context has shown potential for improving the precision of congenital heart defect diagnosis, offering a more automated and objective approach compared to traditional methods[16]. The comparison between human-assisted and DL-based feature extraction methods has also been explored, with deep learning approaches demonstrating superior accuracy in classifying arrhythmias from ECG signals. This highlights the importance of leveraging advanced feature extraction techniques to enhance the overall diagnostic process[17].

Furthermore, ANN have been utilized for predicting cardiovascular diseases based on spectral features extracted from ECG signals. The integration of neural networks with spectral feature extraction has proven effective in identifying key patterns in the ECG data that are indicative of CVDs, leading to more accurate predictions and early intervention[18]. DL-based approaches, such as CNN, have also been successfully applied to ECG signal analysis for automated CVD diagnosis. These models have been optimized to handle the complex patterns present in ECG signals, offering an efficient and reliable tool for cardiovascular risk assessment[19].

Recent advancements in machine learning models for identifying cardiac patients based on their medical conditions have further demonstrated the potential of these models to improve the accuracy of CVD detection. By integrating multiple ML algorithms and optimizing their performance, researchers have developed systems capable of accurately classifying patients with cardiovascular conditions based on ECG data[20]. Another promising approach involves the use of wavelet feature extraction combined with convolutional capsule networks, which have been shown to effectively classify CVDs from ECG signals. This method enhances the feature extraction process, leading to improved classification accuracy[21].

In addition, "empirical mode decomposition" (EMD) has been applied to ECG feature extraction in deep learning models, offering a novel approach to analyzing the intrinsic oscillations within ECG signals. This technique enables the decomposition of the ECG signal into simpler components, which can be more easily processed by deep learning models for CVD classification[22]. Similarly, one-dimensional CNN models have been developed for classifying cardiac arrhythmias from ECG signals, providing a lightweight and efficient solution for real-time cardiovascular disease diagnosis[23].

Combining mathematical models for "heart rate variability" (HRV) mapping with machine learning techniques has also shown promise in predicting sudden cardiac death. This approach leverages both the temporal and frequency-domain characteristics of HRV, enabling more accurate predictions of life-threatening cardiac events[24]. Moreover, a one-dimensional CNN approach has been successfully employed for ECG-based cardiovascular disease classification, offering a high-performance solution for detecting various heart conditions with minimal computational overhead[25].

In conclusion, the use of deep learning and machine learning techniques in ECG signal analysis has significantly advanced the field of cardiovascular disease detection. By leveraging advanced feature extraction methods and optimizing classification algorithms, researchers have developed models that improve the accuracy and efficiency of CVD diagnostics. These innovations hold great promise for enhancing early detection and intervention, ultimately reducing the global burden of cardiovascular diseases.

3. METHODOLOGY

a. Dataset

Dataset consists of ECG recordings aimed at classifying heart rhythms, including both normal and abnormal conditions. The dataset is a valuable resource for developing and testing algorithms that can automatically detect and classify arrhythmias and other cardiac conditions as shown in figure-1,2. It contains recordings from multiple sources, varying in length and sample rates, representing real-world clinical scenarios.

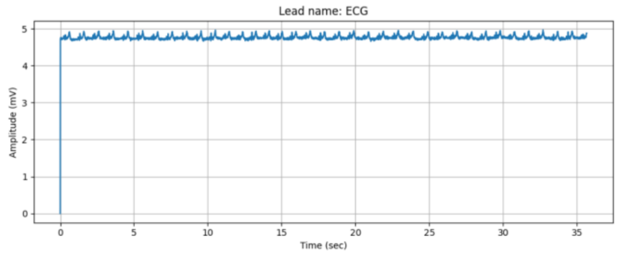

Figure 1 Normal ECG Signal

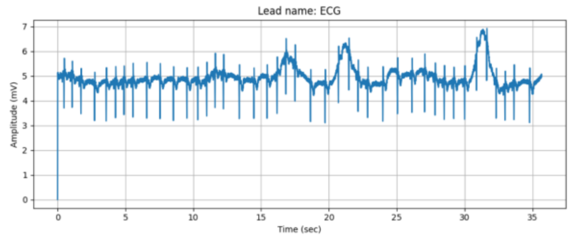

Figure 2 Abnormal ECG Signal

b. Data pre-processing

- **Rename Labels**: In this step, the labels in the dataset are standardized or renamed for consistency and easier interpretation during the model training and evaluation phases. For example, different variations of arrhythmia classifications might be unified under a common label to avoid redundancy and confusion, such as renaming all instances of "irregular rhythm" to "arrhythmia."
- **Noise Removal Using STFT**: The "Short-Time Fourier Transform" (STFT) is used to remove noise from ECG signals. It transforms the signal from the time domain into both time and frequency domains, allowing for analysis of how the signal's frequency content changes over time. By applying a window function and transforming the signal into segments, STFT helps isolate noise and filter it out, preserving the critical features of the ECG signal. The STFT is depicted by following equation:

$$STFT\{x(t)\}(m,\omega) = \int_{-\infty}^{\infty} x(t)w(t-m)e^{-j\omega t}\,dt$$

Where, $x(t)$ = "signal", $w(t-m)$= "window function centered at time m", ω= "frequency", $e^{-j\omega t}$= "complex exponential function".

c. Data balancing using SMOTE

SMOTE is a technique used to address class imbalance by generating synthetic examples for the minority class. Instead of simply duplicating samples, SMOTE creates new synthetic data points by interpolating between existing minority class instances. This helps improve the performance of machine learning models by providing a more balanced dataset.

1. **Selecting k-nearest neighbors:** SMOTE selects a random sample x_i from the minority class and finds its k-nearest neighbors. This is calculated using Euclidean distance:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{n} (x_i^k - x_j^k)^2}$$

Where, $d(x_i, x_j)$= "distance between two data points x_i and x_j" x_i^k= "k^th^ feature of sample x_i "

2. **Generating synthetic samples:** Once the neighbors are identified, a synthetic sample is generated by interpolating between the chosen sample x_i and one of its neighbors x_{nn}

$$x_{new} = x_i + \lambda \times (x_{nn} - x_i)$$

Where, λ= "random number between 0 and 1".

3. **Balancing the dataset:** The process is repeated until the minority class has enough synthetic samples to balance the dataset with the majority class, improving the model's ability to generalize across imbalanced data.

d. Standard feature extraction method

1. **MFCC Features Extraction (Mel Frequency Cepstral Coefficients):**

MFCC is commonly used for extracting frequency-based features from signals, including ECG. It converts signals into a mel scale, which mimics human auditory perception, focusing on key frequencies.

i. Discrete Fourier Transform (DFT): To convert the signal from the time domain to the frequency domain, the signal *x(t)* undergoes DFT:

$$X(f) = \sum_{t=0}^{N-1} x(t) e^{-j2\pi ft/N}$$

Where *X(f)* = "frequency representation", N= "length of the signal"

ii. Mel Scale Transformation: The frequency is then mapped to the mel scale using:

$$m(f) = 2595 \times \log_{10}(1 + \frac{f}{700})$$

2. **DWT Feature Extraction (Discrete Wavelet Transform):**
DWT analyzes the signal by decomposing it into different frequency components, useful for capturing both time and frequency information.

i. DWT coefficients:
The DWT of a signal *x(t)* is represented as:

$$X_{j,k} = \sum_t x(t) \psi_{j,k}(t)$$

Where $\psi_{j,k}(t)$= "wavelet function with j representing the scale" and *k*= "translation".

ii. Inverse DWT:
To reconstruct the signal after feature extraction, the inverse DWT is applied:

$$x(t) = \sum_j \sum_k X_{j,k} \psi_{j,k}(t)$$

e. Proposed novel feature extraction methods: MFCC-DWT Feature Extraction and Fusion

In this combined approach, MFCC and DWT features are extracted separately, and then fused together to enhance the feature set for analysis. MFCC captures the frequency domain's essential characteristics, while DWT captures both frequency and time-domain features. Fusion integrates these complementary features to provide a more comprehensive representation of the ECG signal, improving classification accuracy.

4. DEEP LEARNING MODEL USED

CNN are widely used in signal and image classification due to their ability to automatically learn spatial hierarchies of features. By utilizing convolutional layers, CNNs are adept at detecting patterns and extracting features from raw data, such as ECG signals, without extensive preprocessing. This makes them particularly effective in medical diagnosis, where precise pattern recognition is crucial. However, traditional CNNs can be computationally intensive, making them unsuitable for deployment in resource-constrained environments, such as mobile or IoT devices.

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To address this challenge, lightweight models like VGG16 and MobileNet have been developed. VGG16, although originally a deep and resource-heavy model, can be optimized by reducing its parameters and depth, resulting in a lightweight version. This version maintains its hierarchical feature extraction capabilities while significantly lowering memory and computational requirements. This makes lightweight VGG16 suitable for tasks like ECG classification, where real-time analysis on limited hardware is needed.
MobileNet is another lightweight deep learning model designed specifically for mobile and embedded devices. It uses depthwise separable convolutions, which drastically reduce the number of parameters and computations compared to standard convolutions. Despite its lightweight nature, MobileNet retains strong performance for tasks like image and signal classification. By using these lightweight models, it's possible to deploy advanced CNN-based diagnostic tools in real-time applications, such as wearable health monitors, without sacrificing too much accuracy.

5. RESULTS AND OUTPUTS

5.1. CNN

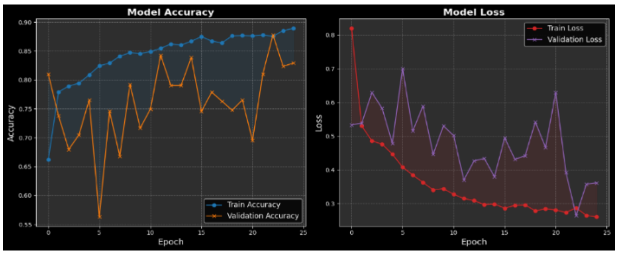

Figure 3 Model accuracy and loss

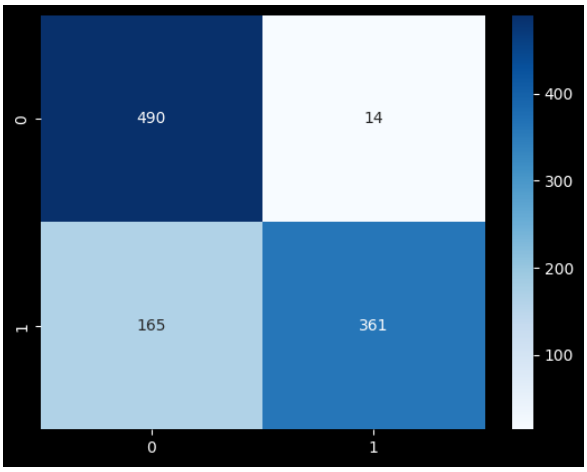

Figure 4 Confusion matrix

5.2. Lightweight MobileNet

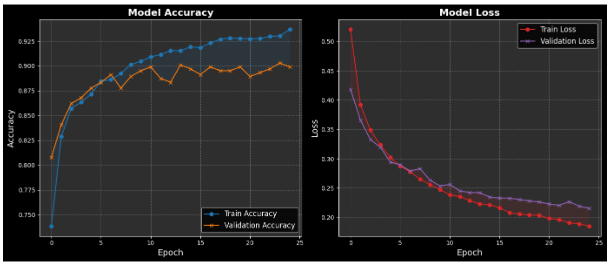

Figure 5 Model Accuracy and loss

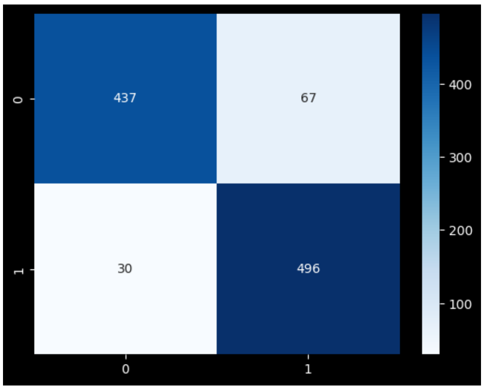

Figure 6 Confusion matrix

5.3. Lightweight VGG16

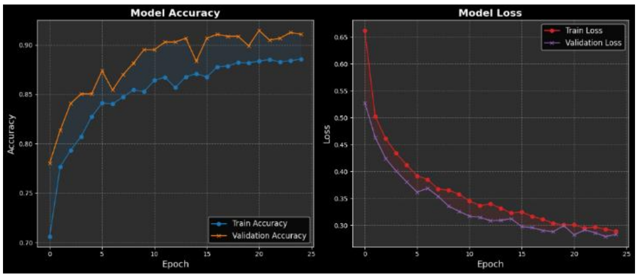

Figure 7 Model accuracy and loss

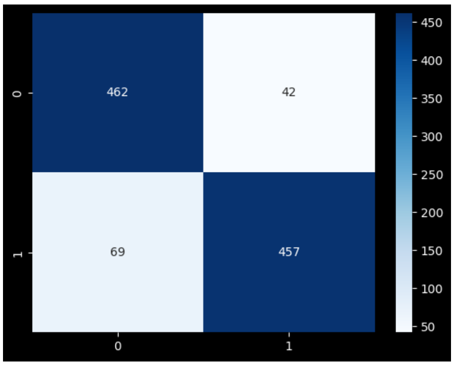

Figure 8 Confusion matrix

5.4. Comparative Analysis

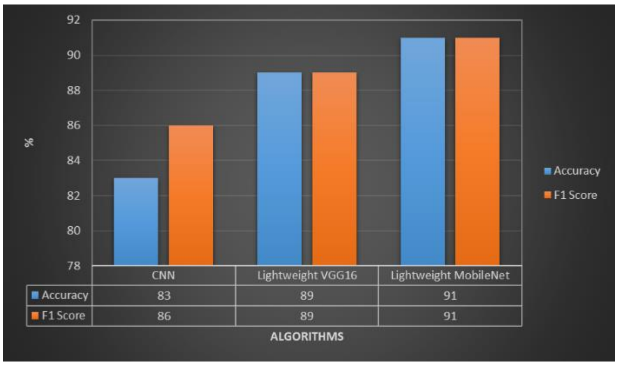

Figure 9 Performance Comparison of Algorithms

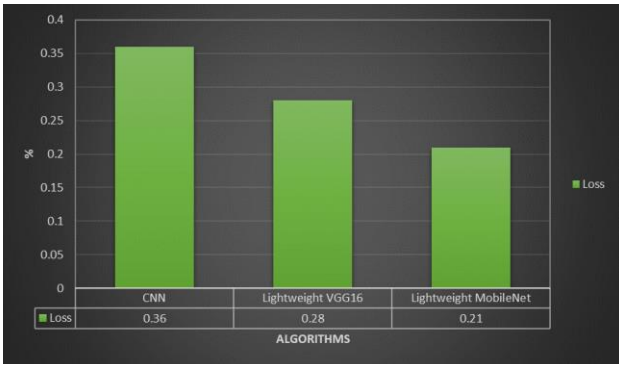

Figure 10 Loss Comparison of Algorithms

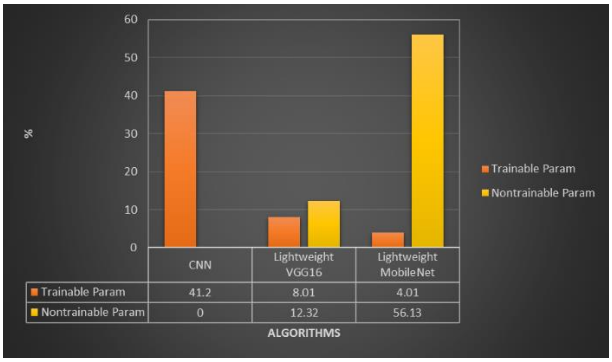

Figure 11 Trainable and Non-Trainable Parameters Comparison of Algorithms

6. RESULT DISCUSSION

The results from Figure 3,4 show the CNN model's performance over 25 epochs in terms of accuracy and loss. The training accuracy (blue line) improves consistently, stabilizing around 0.85, indicating effective learning. However, the validation accuracy (orange line) fluctuates between 0.65 and 0.85, suggesting possible overfitting. Training loss decreases smoothly, while validation loss shows spikes before stabilizing, further indicating generalization issues. The confusion matrix reveals 165 false negatives and 14 false positives, pointing to a need for tuning to enhance sensitivity and balance.

The results of the lightweight MobileNet model over 25 epochs, as seen in Figure 5,6 show consistent improvements in training accuracy, reaching around 0.93. However, the validation accuracy fluctuates, settling around 0.88, indicating some overfitting. Training loss steadily decreases below 0.2, while validation loss, although reducing, remains above 0.3 with minor fluctuations. The confusion matrix (Figure 4) shows 437 true negatives and 496 true positives, with 67 false positives and 30 false negatives. While the model shows promising accuracy, improvements in generalization and sensitivity could further enhance its performance for real-time deployment in constrained environments.

The results of the lightweight VGG16 model show strong performance over 25 epochs, with training accuracy stabilizing around 0.87 and validation accuracy remaining higher, reaching 0.90 by the 15th epoch, suggesting good generalization and minimal overfitting as shown in figure-7,8. The training and validation loss both decrease consistently, stabilizing around 0.3. The confusion matrix reveals 462 true negatives and 457 true positives, with 42 false positives and 69 false negatives. The model demonstrates solid performance with a slight tendency to misclassify positive cases, making it suitable for real-time, resource-constrained deployment.

The results show in figure-9, 10, 11 that Lightweight MobileNet outperforms both CNN and Lightweight VGG16 across multiple metrics. MobileNet achieved the highest accuracy (91%) and F1 score (91%), with the lowest loss (0.21), demonstrating strong generalization and performance. Lightweight VGG16 follows closely with an accuracy of 89% and loss of 0.28, while CNN lags behind with an accuracy of 83% and a higher loss of 0.36. In terms of model complexity, CNN has the highest trainable parameters, while MobileNet strikes a balance between high performance and lower trainable parameters, making it the most efficient for real-time applications.

7. CONCLUSION AND FUTURE SCOPE

The study on feature extraction and fusion of ECG signals using Mel Frequency Cepstral Coefficients (MFCC) and Discrete Wavelet Transform (DWT) for cardiovascular disease diagnosis demonstrates the potential of integrating both time-domain and frequency-domain features to improve classification accuracy. MFCC effectively captures the frequency characteristics of ECG signals, while DWT excels in representing both time and frequency components, making it ideal for detecting subtle variations in heart rhythms. By combining these complementary methods, the resulting fused features provide a more comprehensive representation of the ECG data, enhancing the detection of cardiovascular diseases.

The implementation of this feature extraction and fusion technique, along with the use of lightweight deep learning models like MobileNet and VGG16, has shown promising results in terms of classification accuracy, sensitivity, and loss minimization. The lightweight models, optimized for resource-constrained environments such as IoT and mobile devices, can perform real-time, on-device ECG analysis, enabling early detection and continuous monitoring of cardiovascular conditions. The fusion of MFCC and DWT features ensures that critical information from both the frequency and time domains is retained, contributing to the model's robustness and accuracy in diagnosing cardiovascular diseases.

Future Scope

In the future, the integration of MFCC and DWT could be further enhanced by incorporating additional signal processing techniques, such as “empirical mode decomposition” (EMD) or “principal component analysis” (PCA), to reduce noise and improve feature quality. Also, expanding this approach to include multi-lead ECG signals and testing on larger, more diverse datasets could improve the model's generalization ability. Real-world deployment of these lightweight models in wearable devices or mobile applications could provide real-time, personalized health monitoring, paving the way for continuous, non-invasive cardiovascular disease management and early intervention.

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