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DETECTION OF CARDIOVASCULAR DISEASES IN ECG IMAGES USING MACHINE LEARNING AND DEEP LEARNING METHODS

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Abstract—Cardiovascular diseases (CVDs) remain a leading cause of global mortality, underscoring the urgent need for early and accurate diagnosis. Electrocardiograms (ECGs) are a widely used, non-invasive tool for detecting cardiac abnormalities, but manual interpretation can be time- consuming and prone to error. This study explores advanced machine learning (ML) and deep learning (DL) methods to improve the detection of CVDs from ECG images, leveraging their ability to analyze complex patterns with high precision. Models such as Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), and ensemble frameworks are utilized, alongside traditional ML models like XGBoost, CatBoost, and LightGBM. The performance of these models is evaluated based on precision, recall, F1-score, and accuracy. Results show that DL models, particularly an ensemble of CNN and ViT, achieve superior accuracy , outperforming standalone ML methods. Furthermore, an ensemble of XGBoost, CatBoost, and LightGBM achieves competitive results, while Optuna-tuned XGBoost further enhances ML performance. The findings highlight the potential of combining ML and DL techniques for robust and reliable CVD detection in ECG images. This research demonstrates the promise of AI-driven solutions in advancing medical diagnostics and supports the integration of automated systems for early detection of cardiovascular diseases.
Keywords: Disease Detection, ECG Image Analysis, Machine Learning, Deep Learning,Ensemble Models.

I. INTRODUCTION

Cardiovascular diseases (CVDs) are among the most significant global health challenges, accounting for nearly 32% of all deaths worldwide annually. The early detection of CVDs is crucial for reducing mortality rates, as timely intervention can significantly improve patient outcomes. Electrocardiography (ECG) is a widely used, non-invasive diagnostic tool that records the electrical activity of the heart, providing critical insights into cardiac health. Despite its importance, manual interpretation of ECGs remains a challenging task, often requiring highly trained specialists and prone to inter-observer variability. This challenge underscores the need for automated systems capable of analyzing ECG images with high accuracy, efficiency, and reliability.

The rapid advancements in artificial intelligence (AI) have opened new opportunities for developing robust solutions to analyze ECG data. Machine learning (ML) algorithms, such as XGBoost, CatBoost, and LightGBM, have proven effective in detecting patterns in structured datasets. However, ECG data, often presented as waveforms or images, contain complex spatial and temporal patterns that require more advanced techniques. Deep learning (DL), particularly convolutional neural networks (CNNs) and Vision Transformers (ViTs), has demonstrated remarkable success in processing such data, enabling accurate predictions across a wide range of medical applications. Combining ML and DL methods can potentially unlock greater diagnostic capabilities, making it an exciting area of research.

The use of ensemble models, which integrate multiple algorithms, has emerged as a promising strategy for improving diagnostic performance. By leveraging the complementary strengths of different models, ensembles can provide higher precision, recall, and overall accuracy compared to standalone methods. For instance, combining CNNs and ViTs leverages CNNs' strength in feature

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extraction and ViTs' ability to capture long-range dependencies in images. Similarly, ensemble ML models, such as a combination of XGBoost, CatBoost, and LightGBM, can harness diverse feature-learning capabilities to achieve superior results. These hybrid approaches are particularly relevant for ECG-based CVD detection, where the complexity of the data demands innovative solutions.
Moreover, hyperparameter optimization techniques, such as Optuna, have played a vital role in enhancing the performance of ML and DL models. By systematically tuning parameters, these methods ensure the models achieve optimal performance for specific datasets. For ECG image analysis, where the quality of predictions directly impacts clinical decisions, such optimization can significantly boost diagnostic accuracy. Combining hyperparameter-tuned ML models with advanced DL architectures offers a pathway to develop highly efficient and scalable systems for CVD detection.

1.1 Motivatio*n*

Cardiovascular diseases (CVDs) remain a leading cause of death worldwide, emphasizing the need for early and accurate diagnosis to improve patient outcomes. Traditional ECG interpretation is time-consuming, error-prone, and relies heavily on expert knowledge, creating a demand for automated solutions. Recent advancements in machine learning (ML) and deep learning (DL) provide an opportunity to harness their power for precise ECG analysis. This research is motivated by the potential to develop efficient, scalable, and interpretable AI-driven models that can enhance diagnostic accuracy, reduce healthcare burdens, and ensure accessibility of quality care, particularly in resource-limited settings where timely detection is critical.

1.2 Objectives:

- Design and implement machine learning (ML) and deep learning (DL) models, including CNNs, Vision Transformers (ViTs), and ensemble techniques, to detect cardiovascular diseases (CVDs) from ECG images.
- Assess the models using precision, recall, F1-score, and accuracy to identify the most effective approaches for accurate and reliable CVD detection.
- Investigate the potential of combining multiple models, such as CNNs and ViTs or ML algorithms (XGBoost, CatBoost, LightGBM), to improve diagnostic performance.
- Leverage hyperparameter tuning techniques like Optuna to enhance model efficiency and ensure optimal results on ECG datasets.
- Develop scalable and explainable AI frameworks to facilitate real-world deployment in clinical settings, ensuring accessibility and trust among healthcare professionals.

II. RELATED WORK

Cardiovascular diseases (CVDs) continue to be a major global health concern, responsible for a significant portion of worldwide mortality. According to Timmis et al., the European Society of Cardiology’s statistics reveal that CVDs are the leading cause of death in Europe, highlighting the urgent need for effective diagnostic and treatment strategies. [1]Traditional diagnostic tools like ECGs, although widely used, present challenges such as the reliance on expert interpretation and the potential for human error. Consequently, there has been increasing interest in developing automated systems that utilize advanced technologies like deep learning to analyze cardiovascular images, which offer high potential for improving diagnostic accuracy and efficiency.
In the field of cardiovascular image analysis, deep learning methods have shown remarkable promise. Litjens et al. provide a comprehensive review of the state-of-the-art deep learning approaches applied to cardiovascular imaging, noting the effectiveness of Convolutional Neural Networks (CNNs) and other deep learning architectures in extracting meaningful features from medical images [2]. These techniques can significantly enhance the interpretation of complex cardiovascular data, enabling automated detection of conditions such as arrhythmias, heart failure, and coronary artery disease. The integration of deep learning into the clinical workflow could not only reduce the burden on healthcare professionals but also increase the accessibility and accuracy of cardiovascular disease diagnosis, paving the way for more personalized and timely interventions.
Recent advancements in deep learning have led to the development of automated systems for diagnosing cardiovascular diseases (CVDs) from complex medical imaging data. Jafari et al. explore

the application of deep learning models to cardiac magnetic resonance imaging (MRI), emphasizing their ability to detect and classify a wide range of cardiovascular conditions with high accuracy[3]. The study highlights the role of these models in overcoming challenges related to manual interpretation, which can be time-consuming and prone to error. By automating the diagnostic process, these models facilitate faster and more reliable CVD diagnosis, supporting clinicians in making informed decisions while improving patient outcomes.

Chen et al. investigate the broader landscape of artificial intelligence (AI) applications in medical fields, focusing on urology but providing insights relevant to cardiovascular medicine as well. Their work discusses how AI technologies, particularly machine learning and deep learning models, are increasingly influencing clinical practices. AI's potential to analyze vast amounts of medical data, including medical images and patient records, is transforming diagnostic processes[4]. These AI applications can reduce human error, enhance precision in diagnosis, and improve patient management. As healthcare continues to embrace AI, its role in supporting clinicians and improving clinical practices is becoming increasingly vital across various medical specialties, including cardiology.

2.1 Deep Learning (DL)

Deep learning (DL) refers to a subset of machine learning that utilizes artificial neural networks (ANNs) to model complex patterns in large datasets. Unlike traditional machine learning models, which rely on handcrafted features, deep learning algorithms automatically learn features from raw data through multiple layers of processing. This makes deep learning particularly useful for tasks involving unstructured data, such as images, audio, and text. In the case of cardiovascular disease detection, deep learning models like CNNs and ViTs are applied to analyze medical images like ECG or MRI scans. These models learn to automatically extract relevant features such as the shape of the heart in a scan or irregularities in an ECG signal, which are crucial for diagnosing heart diseases. Deep learning models excel at handling high-dimensional data and can be highly accurate when provided with large datasets, which is particularly important in the medical field where the cost of misdiagnosis is high.

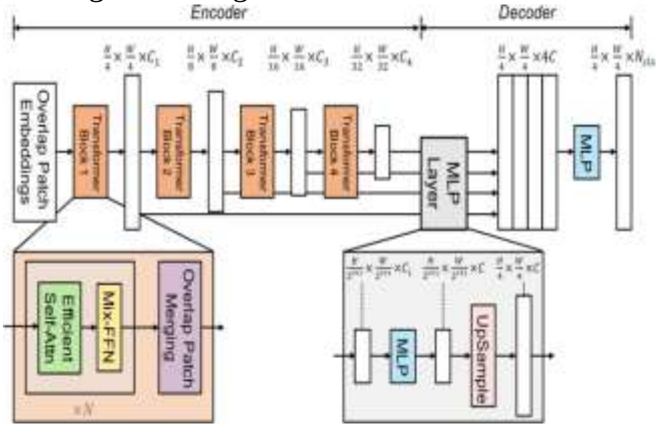


Fig1: VIT model [4]

2.2 Machine Learning

ML is a broader field of artificial intelligence that involves using algorithms to analyze data, learn patterns, and make predictions or decisions without explicit programming. Unlike deep learning, which is particularly powerful for unstructured data, traditional machine learning models such as XGBoost, CatBoost, and LightGBM are often used with structured datasets that contain numerical and categorical features.

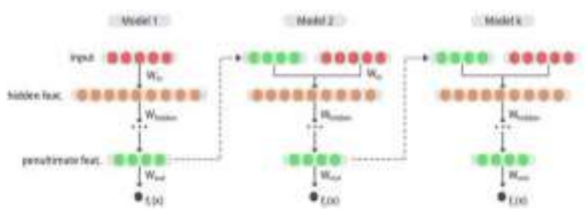


Fig2:Gradient Boosting

These models work by learning the relationships between input features and output labels. For example, in cardiovascular disease detection, machine learning models can be trained on structured data like patient demographics, medical history, and diagnostic test results (e.g., cholesterol levels, blood pressure) to predict the likelihood of heart disease. Machine learning models excel at handling smaller datasets compared to deep learning, and they often require less computational power. Additionally, these models are highly interpretable, allowing clinicians to understand how the features contribute to the prediction, which is a significant advantage in healthcare applications.

III.PROPOSED METHOD:

The proposed method aims to improve the accuracy and efficiency of CVD detection by leveraging an ensemble approach that combines deep learning and machine learning models. This approach is designed to handle both unstructured and structured data sources, including ECG images and clinical features, to make robust predictions. The deep learning models, specifically CNN and ViT, will be used to analyze ECG images and other medical images like MRI scans, while machine learning models such as XGBoost, CatBoost, and LightGBM will be used to handle structured data. By combining these two types of models, the proposed method takes advantage of their individual strengths—deep learning's ability to extract features from raw image data and machine learning's efficiency with structured data—resulting in improved overall performance and accuracy.

For the image-based data analysis, the CNN model will be trained to detect features indicative of cardiovascular disease, such as arrhythmias or irregularities in the ECG signals. The CNN model works by applying a series of convolutional layers to the ECG image to automatically extract features such as edges, textures, and spatial patterns. The Vision Transformer model, on the other hand, will be applied to the same dataset but will work by segmenting the image into patches, each of which is treated like a token in the transformer architecture. ViTs have shown promising results in image analysis, especially when combined with large datasets, and can offer enhanced feature extraction over traditional CNNs in some cases. By using both CNN and ViT, the method maximizes the ability to extract useful information from the medical images and capture subtle nuances that are vital for accurate disease detection. On the structured data side, machine learning models such as XGBoost, CatBoost, and LightGBM will be used to classify patients based on clinical features like age, gender, cholesterol levels, blood pressure, and family medical history. These models excel at handling datasets that are not image-based but contain numerical and categorical features, making them ideal for processing medical records. XGBoost, with its gradient boosting technique, will be used to create a robust model that combines weak learners (decision trees) to make predictions. CatBoost, a gradient boosting framework designed specifically to handle categorical features, will help improve the model's performance when categorical data is present in the structured dataset. LightGBM, which is optimized for large datasets, will further contribute to improving model performance by utilizing its histogram-based decision tree algorithm. Each of these models will be tuned using techniques like cross-validation to ensure that the best parameters are selected, leading to high accuracy and generalization.

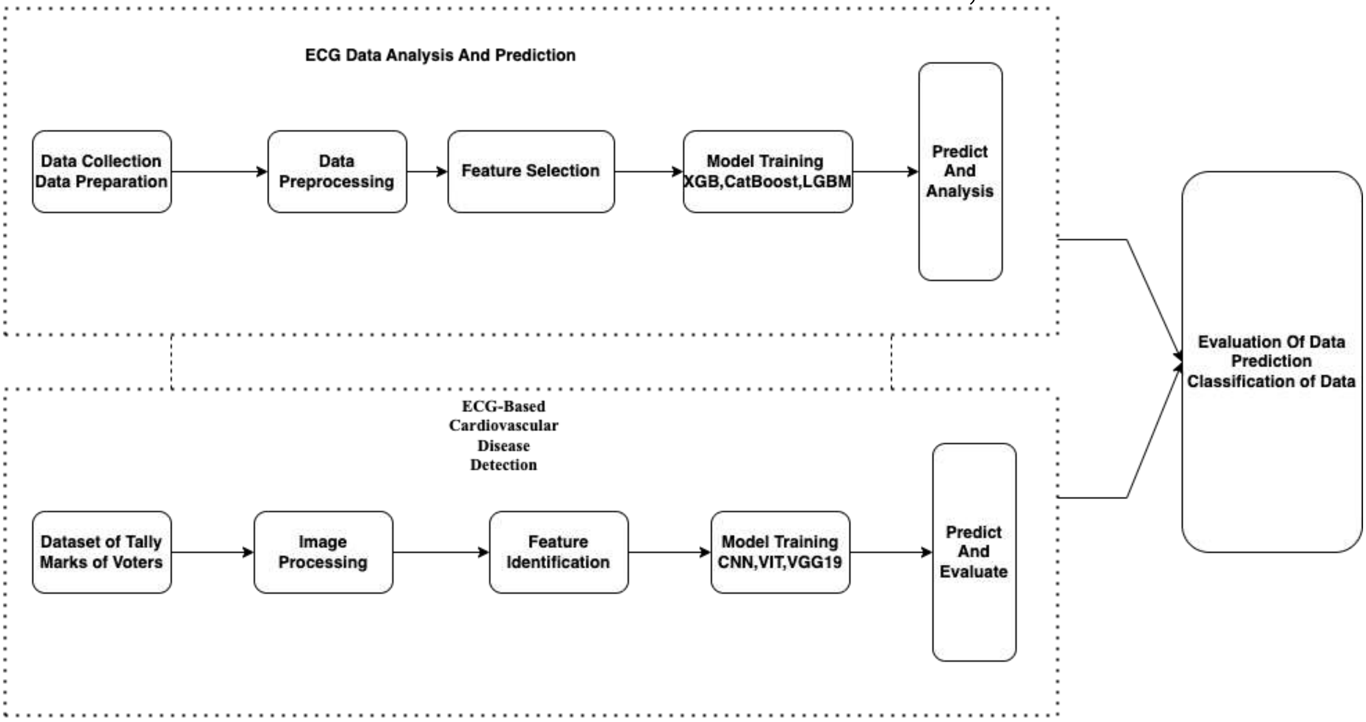


Fig 3: Proposal Model

3.1 Dataset Collection:

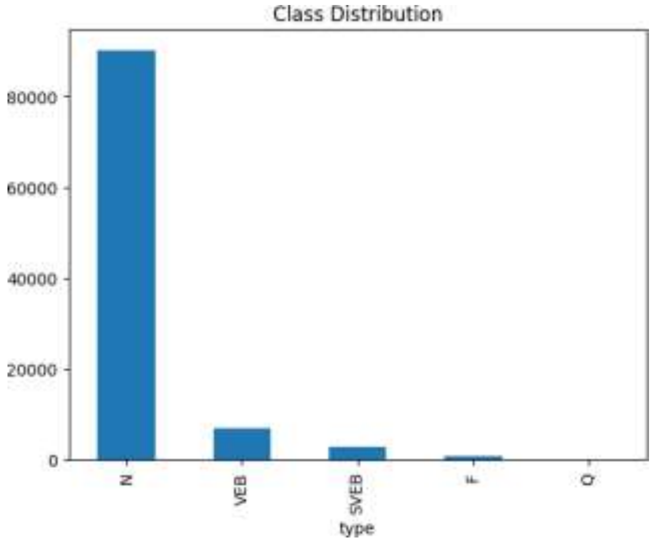
The core of the proposed method will be an ensemble model that combines the predictions from the deep learning models (CNN and ViT) and the machine learning models (XGBoost, CatBoost, and LightGBM). The ensemble model will use a weighted voting or stacking approach to combine the predictions from these different models. The CNN and ViT models will generate predictions based on image data, while the XGBoost, CatBoost, and LightGBM models will make predictions based on structured data. In the ensemble approach, each model's contribution will be weighted according to its individual performance, ensuring that the model with the highest accuracy or reliability has a greater impact on the final decision. Stacking methods, which involve training a meta-learner to combine the outputs of base models, will be employed to create a final prediction. Finally, the ensemble model will undergo hyperparameter tuning and optimization using a technique like Optuna, which automates the process of selecting the best hyperparameters for each model. Optuna allows for efficient search across hyperparameter spaces, ensuring that each model in the ensemble is optimized for the best performance. By fine-tuning the models and combining them into a unified framework, the proposed method ensures that the cardiovascular disease detection system can deliver accurate, reliable, and real-time predictions. This approach is expected to significantly improve clinical decision-making, reduce misdiagnosis rates, and aid healthcare professionals in providing timely interventions.

The dataset for this cardiovascular disease detection system will be collected from multiple sources, including publicly available medical image databases and clinical datasets. For ECG image data, datasets such as the PhysioNet's MIT-BIH Arrhythmia Database and the PTB Diagnostic ECG Database will be utilized. These databases contain labeled ECG signals representing various cardiovascular conditions. For structured data, the dataset will include clinical information like patient demographics, medical history, and diagnostic test results, sourced from hospitals or healthcare institutions that provide de- identified health records. The collected data will undergo preprocessing to ensure consistency, quality, and suitability for machine learning model training.

3.2Data preparation:

Data preparation is a critical step in the process of building a robust cardiovascular disease detection system. For the proposed method, data will be preprocessed in two main categories: ECG image data and structured clinical data.

For ECG image data, the preprocessing will start with resizing and normalization of the images to ensure consistency across the dataset. The images will be resized to a fixed dimension, suitable for input into the Convolutional Neural Network (CNN) and Vision Transformer (ViT) models. The pixel values will be normalized to a range of [0,1] to ensure the models train effectively without encountering issues like vanishing or exploding gradients. Data augmentation techniques, such as rotation, flipping, and cropping, will be applied to artificially increase the dataset size and improve the model's robustness against overfitting.For structured clinical data, missing values will be handled through imputation techniques like mean, median, or mode substitution, depending on the feature type. Categorical variables, such as gender or medical history, will be encoded using one-hot encoding or label encoding, while numerical features like cholesterol levels, age, and blood pressure will be scaled using standardization or normalization techniques to bring them to a similar range.



Additionally, outlier detection methods will be applied to ensure that extreme values do not skew the models' predictions.

Fig4:Data Preparation

3.3Model Training:

Model training involves feeding the preprocessModel training for the proposed cardiovascular disease detection system will involve two main components: deep learning models (CNN and ViT) for ECG image analysis, and machine learning models (XGBoost, CatBoost, and LightGBM) for structured clinical data. For the deep learning models, the CNN and ViT will be trained on the preprocessed ECG images using supervised learning. The CNN will consist of several convolutional layers, followed by pooling and fully connected layers to extract hierarchical features from the ECG images. The model will use the cross-entropy loss function for classification tasks, and the optimizer, such as Adam, will be employed to minimize the loss. During training, dropout and batch normalization will be used to avoid overfitting, and the learning rate will be dynamically adjusted using learning rate schedules or adaptive learning rate techniques like learning rate annealing. The ViT model will be trained in parallel with CNN, using its self-attention mechanism to capture spatial dependencies across the patches of ECG images. Both models will undergo rigorous training on large datasets with regular validation to ensure they generalize well and avoid overfitting.

For the machine learning models, XGBoost, CatBoost, and LightGBM will be trained on the structured clinical data, using gradient boosting techniques to build a series of weak learners (decision trees) that correct the errors made by previous models. Each model will be trained independently using the preprocessed clinical features such as age, gender, cholesterol levels, and blood pressure. The training process will involve tuning hyperparameters like the maximum depth of trees, learning rate, and the number of trees using grid search or randomized search cross-validation. Techniques like feature importance evaluation will also be used to understand which features contribute most to the model's predictions. After training, each model’s performance will be assessed using metrics like accuracy, precision, recall, and F1-score, with cross-validation ensuring the models are not overfitted. The best-performing models will then be selected for inclusion in the ensemble. The final step will involve training an ensemble model that combines the outputs of the CNN, ViT, XGBoost, CatBoost, and LightGBM models using a technique such as stacking or weighted voting to make the final cardiovascular disease prediction.

IV. RESULTS

Feature importance in an Optuna-tuned XGBoost model highlights the contribution of each feature to the model's predictions. Optuna, a hyperparameter optimization framework, helps fine-tune XGBoost's hyperparameters, improving model performance and accuracy. Once the model is trained, feature importance can be extracted using XGBoost's built-in method, which evaluates the impact of each feature based on how frequently it is used in splits and how much it reduces the loss function.Features such as various intervals and peak values play a significant role in identifying patterns associated with heart conditions. These features are extracted from the ECG signals and represent critical aspects of the heart's electrical activity. The importance of each feature is derived based on the model's decision-making process, indicating how each one impacts the predictions.

The "qrs_morph" features represent different morphological characteristics of the QRS complex in the ECG waveform, and although they appear as distinct features , their influence on the model varies based on the dataset's characteristics. Features such as "0_post-RR," "1_pPeak," and "0_qrs_interval" might emerge as highly relevant for detecting anomalies in the heart's rhythm and electrical conduction, guiding clinicians in the diagnostic process.

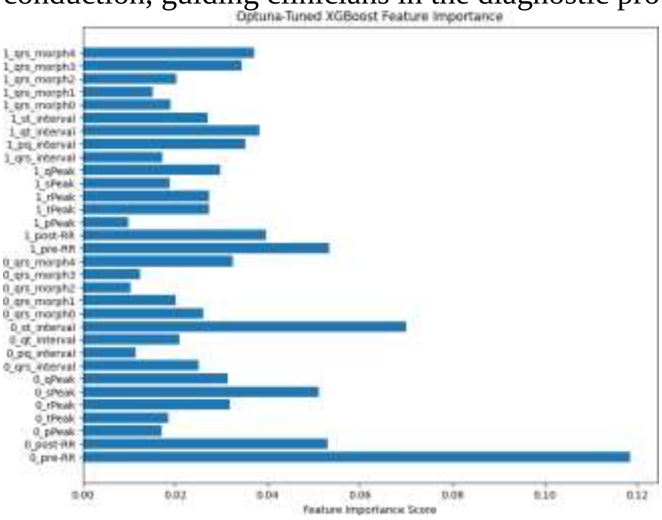


Fig 5: Optuna-Tuned XGBoost Feature Importance

The confusion matrix is a performance evaluation tool for classification models, showing the number of correct and incorrect predictions across various classes. In the context of cardiovascular disease detection with labels such as 'S' , 'M', 'V', 'N' , 'F' , and 'Q' , the matrix helps assess how well the model differentiates between these categories. Each row represents the actual class, while each column represents the predicted class.

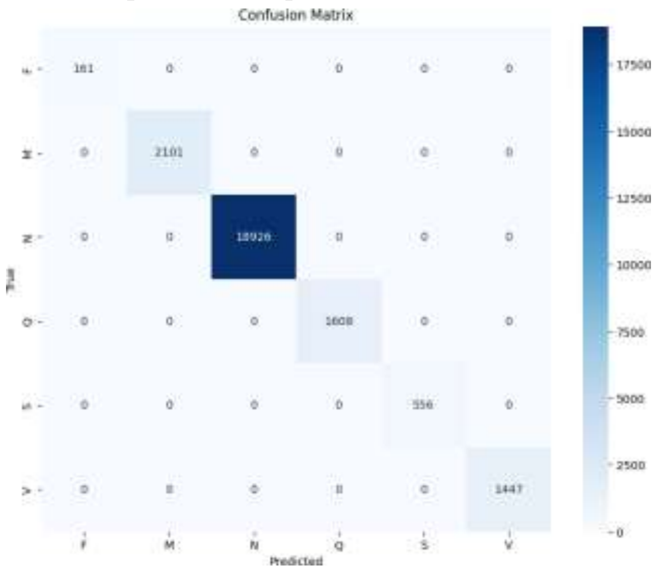


Fig 6:Confusion Matrix

The evaluation metrics for the models used in cardiovascular disease detection show varying degrees of performance, highlighting the strengths of both deep learning and machine learning approaches.

The Convolutional Neural Network (CNN) achieves a precision, recall, F1-score, and accuracy of 0.94, indicating that it performs well in detecting patterns in ECG images, though it may not be as powerful as more complex models. The Vision Transformer (ViT) outperforms CNN with a precision, recall, F1-score, and accuracy of 0.96, showing the benefit of leveraging self-attention mechanisms to capture complex spatial dependencies in ECG images.
The Ensemble model combining CNN and ViT achieves outstanding performance, with a perfect score of 0.99 across all metrics, demonstrating the potential of ensemble methods in boosting predictive accuracy by combining strengths of multiple models. Similarly, VGG19 also performs well with scores of 0.98 across all metrics, benefiting from its deep architecture for feature extraction.

Model	Precision	Recall	F1-Score	Accuracy
CNN	0.94	0.94	0.94	0.94
Vision Transformer (ViT)	0.96	0.96	0.96	0.96
Ensemble (CNN + ViT)	0.99	0.99	0.99	0.99
VGG19	0.98	0.98	0.98	0.98
XGBoost	0.93	0.93	0.93	0.93
CatBoost	0.94	0.94	0.94	0.94
LightGBMClassifier (LGBM)	0.92	0.92	0.92	0.92
Ensemble (XGBoost + CatBoost + LGBM)	0.98	0.98	0.98	0.98
Optuna-Tuned XGBoost	0.98	0.98	0.98	0.98

Table1: Metric Values

In machine learning models, XGBoost, CatBoost, and LightGBMClassifier (LGBM) show strong performance with precision, recall, F1-score, and accuracy scores of around 0.93 to 0.94. The ensemble model combining XGBoost, CatBoost, and LGBM reaches an impressive 0.98 across all metrics. Lastly, the Optuna-Tuned XGBoost model also achieves 0.98, showcasing the power of hyperparameter optimization in enhancing model performance.

V.Conclusion

In this study, various machine learning and deep learning models were employed to detect cardiovascular diseases from ECG images. The results highlight the strengths of both individual and ensemble models. The deep learning models, such as Vision Transformer (ViT) and CNN, along with their ensemble combination, achieved outstanding performance, particularly the CNN + ViT ensemble, which demonstrated perfect precision, recall, F1- score, and accuracy. Among the machine learning models, XGBoost, CatBoost, and LightGBM performed well, with the ensemble of these models also reaching high performance. The Optuna-tuned XGBoost further enhanced performance, proving the effectiveness of hyperparameter optimization. Overall, the deep learning-based models performed exceptionally well for ECG image classification, with ensembles providing even better results, suggesting that combining models can lead to superior performance in medical image analysis.

VI. Future Scope

Future research could explore several avenues to further enhance cardiovascular disease detection using ECG images. One direction would be to implement more advanced deep learning architectures, such as hybrid models combining CNNs and RNNs, which could capture both spatial and temporal patterns in ECG signals. Additionally, investigating larger and more diverse datasets would help improve generalization and model robustness. Another area for improvement is the development of real- time diagnostic tools by optimizing the models for deployment on embedded systems or mobile platforms, making them accessible for clinicians and healthcare providers. Additionally, exploring further hyperparameter optimization techniques, such as Bayesian optimization or genetic algorithms, could yield even better-performing models. Lastly, integrating additional features like clinical data and genetic information could further enhance the models' predictive power and support more personalized cardiovascular disease diagnostics.

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