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A Robust Ensemble Machine Learning Framework for Multi-Class Cardiovascular Disease Detection using ECG Images

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Abstract— Cardiovascular diseases (CVDs) continue to be the leading cause of death globally, creating an urgent need for faster and more accessible diagnostic tools. Although electrocardiograms (ECGs) play a crucial role in detecting cardiac abnormalities, their interpretation often requires specialized expertise and can be time-consuming. To address these challenges, this paper proposes a robust ensemble machine learning framework for multi-class cardiovascular disease detection using ECG image-derived signals. The system processes standard 12-lead ECG images by performing grayscale conversion, noise and gridline removal, and contour-based lead extraction to obtain one-dimensional cardiac signals. These signals are normalized and refined using Principal Component Analysis (PCA) to improve classification performance. Multiple machine learning algorithms, including K-Nearest Neighbors, Logistic Regression, Support Vector Machine, Random Forest, Naïve Bayes, and XGBoost, are trained and optimized, and their outputs are combined using a stacking-based ensemble approach.

The model classifies ECG data into four categories: Normal, Abnormal Heartbeat, Myocardial Infarction, and History of Myocardial Infarction. The final system is deployed through a Streamlit-based web application, enabling rapid and user-friendly cardiac screening. The results demonstrate the potential of the proposed approach in supporting efficient and scalable heart disease detection.

Keywords— Electrocardiogram (ECG), Cardiovascular Disease Detection, Ensemble Machine Learning, Signal Extraction, Principal Component Analysis (PCA), Multi-Class Classification.

I. INTRODUCTION

A. Background and Motivation

Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, accounting for millions

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of deaths annually. Early detection plays a critical role in preventing severe complications and improving patient survival rates. Among the various diagnostic tools available, the electrocardiogram (ECG) is one of the most widely used and cost-effective techniques for monitoring heart rhythm and electrical activity. The standard 12-lead ECG provides comprehensive information about cardiac function and is routinely used in clinical practice.

B. Challenges in Manual ECG Interpretation

Despite its clinical importance, ECG interpretation requires significant expertise and experience. The increasing number of cardiac patients, especially in rural and resource-limited regions, creates diagnostic bottlenecks due to the limited availability of trained cardiologists. Additionally, manual interpretation is time-consuming and may be affected by human fatigue or variability in analysis. Subtle waveform abnormalities can sometimes be overlooked, potentially delaying critical diagnosis and treatment.

C. Role of Artificial Intelligence in Cardiac Diagnosis

Recent advancements in artificial intelligence (AI) and machine learning (ML) have shown promising results in medical image and signal analysis. Automated systems can assist clinicians by providing rapid and consistent interpretations of diagnostic data. While several studies focus on deep learning approaches applied directly to raw ECG signals, comparatively fewer works explore structured machine learning techniques using ECG images transformed into analyzable signal representations.

D. Contribution of the Proposed Work

To address these challenges, this study proposes a robust ensemble machine learning framework for multi-class cardiovascular disease detection using ECG image-derived signals. The system converts 12-lead ECG images into one-dimensional signals through preprocessing and contour-based extraction techniques. Feature engineering and dimensionality reduction are applied to enhance classification performance. The proposed framework classifies ECG data into four clinically relevant categories: Normal, Abnormal Heartbeat, Myocardial Infarction, and History of Myocardial Infarction. Furthermore, the developed model is deployed through a web-based interface to enable rapid and accessible cardiac screening.

II. LITERATURE REVIEW

A. Deep Learning Approaches for ECG-Based Diagnosis

Recent years have witnessed substantial progress in the application of artificial intelligence for automated ECG interpretation. Ansari et al. (2023) provided a comprehensive overview of deep learning architectures for arrhythmia detection, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based models. Their review demonstrated that deep learning methods are highly effective in capturing complex temporal and morphological patterns in ECG signals. However, most of these approaches operate directly on digitally recorded raw ECG signals, requiring structured datasets and high computational resources. Such dependency limits their applicability in scenarios where only ECG images or printed reports are available.

B. ECG Image Processing and Waveform Segmentation

In addition to signal-based approaches, researchers have explored ECG image processing techniques to extract clinically relevant waveform information. Joung et al. (2024) proposed a deep learning-based segmentation framework using U-Net architectures to accurately delineate P, QRS, and T wave components. Their method achieved high segmentation accuracy and highlighted the importance of precise waveform extraction before classification. While the study demonstrated strong performance in segmentation tasks, its primary focus remained waveform delineation rather than multi-class cardiovascular disease classification. Moreover, deep learning-based segmentation models often require extensive annotated data and computational resources.

C. Clinical Deployment and Practical Considerations

Beyond model accuracy, real-world deployment and clinical integration remain critical challenges. Lin et al. (2025) discussed the transition of AI-enabled electrocardiography from research environments to

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clinical practice. Their work emphasized validation strategies, reliability, interpretability, and integration with healthcare information systems. Although the study addressed deployment challenges comprehensively, it did not provide a structured framework combining ECG image processing with traditional ensemble machine learning techniques for scalable multi-class disease detection.

D. Research Gap and Motivation

Although existing studies have achieved significant success using deep learning models on raw ECG signals, limited research has focused on transforming ECG images into structured one-dimensional signals suitable for traditional machine learning frameworks. Furthermore, comparatively fewer studies investigate ensemble-based classification techniques for multi-class cardiovascular disease detection using ECG image-derived data. Deep learning methods, while powerful, may require large datasets and high computational cost, making them less accessible in resource-constrained settings.

To address these limitations, the present study proposes a robust ensemble machine learning framework that converts standard 12-lead ECG images into analyzable signals through contour-based extraction and preprocessing techniques. By integrating feature engineering, dimensionality reduction, and ensemble classification, the proposed approach aims to provide a computationally efficient, scalable, and clinically adaptable solution for automated cardiovascular disease detection.

III. PROPOSED METHODOLOGY

A. System Overview

The proposed framework is designed to automatically classify cardiovascular conditions from standard 12-lead ECG images using an ensemble machine learning approach. The overall system consists of multiple sequential stages, including image preprocessing, lead segmentation, signal extraction, feature engineering, dimensionality reduction, and multi-class classification. The complete pipeline converts raw ECG images into structured numerical representations suitable for machine learning analysis.

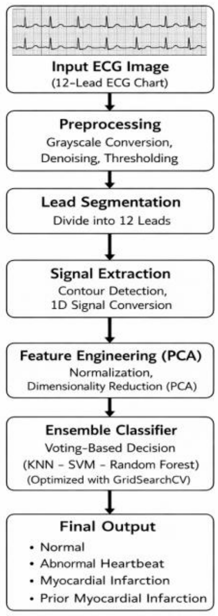

Fig. 1. Overall architecture of the proposed ECG classification framework.

B.Image Preprocessing and Signal Extraction

Input ECG images are converted to grayscale and resized to a uniform resolution. Noise and background gridlines are removed using thresholding and filtering **techniques, followed by binary conversion to enhance** waveform visibility.Each image is segmented into its 12 individual leads. Contour detection is applied to trace waveform boundaries, and the extracted coordinates are transformed into one-dimensional (1D) signal representations. This step enables the conversion of visual ECG patterns into structured numericalfeatures.

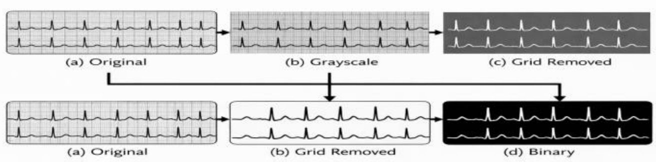

Fig. 2. ECG image preprocessing steps: (a) Original Image, (b) Grayscale Image, (c) Grid Removed, (d) Binary Image.

Fig. 2. ECG image preprocessing steps: (a) Original Image, (b) Grayscale Image.

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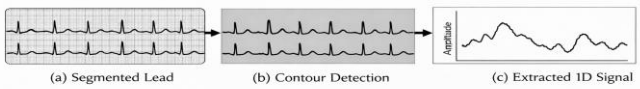

Fig. 3. Contour-based signal extraction and corresponding 1D Signal representation.

C. Feature Engineering

The extracted signals are normalized using MinMax scaling. To reduce feature redundancy and improve computational efficiency, Principal Component Analysis (PCA) is applied to obtain a compact and informative feature representation.

D. Ensemble-Based Classification

Multiple machine learning classifiers, including K-Nearest Neighbors, Logistic Regression, Support Vector Machine, Random Forest, Naïve Bayes, and XGBoost, are trained and optimized using GridSearchCV. A stacking-based ensemble model combines the predictions of individual classifiers to enhance robustness and accuracy.

The system performs multi-class classification across four categories: Normal, Abnormal Heartbeat, Myocardial Infarction, and History of Myocardial Infarction.

E. Deployment

The trained ensemble model is deployed through a Streamlit-based web application, enabling users to upload ECG images and obtain classification results in real time.

IV. IMPLEMENTATION DETAILS

A. Development Environment

The proposed ECG classification framework was implemented using **Python** as the primary programming language. Image preprocessing and contour-based signal extraction were performed using **OpenCV** and **scikit-image** libraries. Numerical computation and data handling were carried out using **NumPy** and **Pandas**.

Machine learning models were developed using the **scikit-learn** framework, and gradient boosting was implemented using the **XGBoost** library. Hyperparameter optimization was performed using **GridSearchCV** with cross-validation to obtain optimal model configurations. All experiments were conducted in a cloud-based development environment to ensure sufficient computational resources for training and evaluation.

B. ECG Image Processing Pipeline

Each ECG image was first converted from RGB to grayscale to reduce computational complexity. Noise reduction was applied using Gaussian filtering, followed by thresholding techniques to enhance waveform visibility and suppress background gridlines.

The preprocessed ECG image was segmented into 12 individual leads. Contour detection algorithms were applied to trace waveform boundaries. The extracted contour coordinates were transformed into normalized one-dimensional (1D) signal representations for each lead.

C. Feature Construction and Dimensionality Reduction

The extracted 1D signals from all 12 leads were combined to form a consolidated feature vector. MinMax normalization was applied to ensure uniform scaling of features.

To reduce redundancy and improve computational efficiency, **Principal Component Analysis (PCA)** was applied to the feature set. The dimensionality reduction process preserved **99.5% of the total variance**, ensuring that essential signal characteristics were retained while reducing feature dimensionality.

D. Model Training and Ensemble Strategy

Multiple supervised machine learning classifiers were implemented and evaluated, including:

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- K-Nearest Neighbors (KNN)
- Logistic Regression
- Support Vector Machine (SVM)
- Random Forest
- XGBoost

Hyperparameter tuning was performed using GridSearchCV to optimize model parameters.

To improve robustness and classification performance, a **voting-based ensemble classifier** was developed by combining KNN, SVM, and Random Forest models. The final prediction was determined using majority voting across the base classified

E. Model Serialization and Deployment

After training and validation, the best-performing ensemble model was serialized using the pickle library and saved for inference.

The trained model was integrated into a web-based application that allows users to upload ECG images. The uploaded image undergoes automatic preprocessing, signal extraction, feature transformation, and classification. The system outputs one of four classes:

- Normal
- Abnormal Heartbeat
- Myocardial Infarction
- Prior Myocardial Infarction

The entire pipeline operates in real time, enabling automated multi-class cardiovascular disease detection.

V. RESULTS AND DISCUSSION

A. Performance Evaluation Strategy

The proposed ECG classification framework was evaluated using standard supervised learning evaluation metrics, including accuracy, precision, recall, and F1-score. Hyperparameter tuning was performed using GridSearchCV to ensure optimal model performance and reduce overfitting.

The performance of individual classifiers was compared with the proposed voting-based ensemble model to analyze improvements in classification robustness.

B. Effect of Dimensionality Reduction

Principal Component Analysis (PCA) was applied prior to classification to reduce feature dimensionality while retaining essential signal characteristics.

The PCA transformation preserved **99.5% of the total variance**, ensuring minimal information loss. Dimensionality reduction significantly improved computational efficiency while maintaining classification performance.

This demonstrates that redundant and correlated features can be effectively eliminated without compromising diagnostic information.

C. Classifier Comparison

Multiple classifiers, including KNN, Logistic Regression, SVM, Random Forest, and XGBoost, were evaluated.

The voting-based ensemble classifier demonstrated improved stability and generalization compared to individual base models. By combining predictions from multiple learners, the ensemble reduced model variance and enhanced classification consistency across all four ECG categories.

D. Confusion Matrix Analysis

The confusion matrix of the ensemble classifier (shown in Fig. X) illustrates the distribution of correctly and incorrectly classified instances across the four classes:

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- Normal
- Abnormal Heartbeat
- Myocardial Infarction
- Prior Myocardial Infarction

The diagonal values represent correctly classified samples, while off-diagonal elements indicate misclassifications.

The results indicate that the ensemble model effectively distinguishes between normal and pathological ECG patterns, with improved detection of myocardial infarction-related classes.

E. Discussion

The experimental results confirm that combining contour-based signal extraction with ensemble machine learning provides a robust approach for multi-class cardiovascular disease detection.

The integration of PCA reduced computational complexity while maintaining signal integrity. The ensemble classifier further improved predictive reliability by aggregating multiple model outputs.

These findings suggest that the proposed system can serve as a supportive diagnostic tool for automated ECG interpretation in clinical environments.

VI. CONCLUSION

In this work, a robust ensemble-based machine learning framework for multi-class cardiovascular disease detection using ECG images was presented. The proposed system integrates structured image preprocessing, contour-based signal extraction, feature normalization, and dimensionality reduction using Principal Component Analysis (PCA) to construct an efficient feature representation.

Multiple supervised classifiers were evaluated, and a voting-based ensemble model was developed to enhance predictive robustness and stability. The dimensionality reduction process retained 99.5% of the total variance, ensuring minimal information loss while improving computational efficiency. The ensemble approach

demonstrated improved classification consistency across the four ECG categories: Normal, Abnormal Heartbeat, Myocardial Infarction, and Prior Myocardial Infarction.

The experimental findings indicate that combining contour-based signal extraction with ensemble learning provides a reliable and scalable solution for automated ECG interpretation. The proposed framework has the potential to support early cardiovascular disease detection and assist clinical decision-making in healthcare environments.

VII. FUTURE WORK

The proposed ensemble-based ECG classification framework demonstrates promising performance for multi-class cardiovascular disease detection. However, several enhancements can be explored in future research.

First, the current system relies on traditional machine learning models combined with contour-based signal extraction. Future work may investigate the integration of deep learning architectures such as Convolutional Neural Networks (CNNs) and hybrid CNN–LSTM models for automatic feature learning directly from ECG images or raw signals.

Second, expanding the dataset with larger and more diverse ECG samples from multiple clinical sources can improve model generalization and robustness across different patient populations.

Third, real-time ECG signal processing from wearable devices and IoT-enabled monitoring systems can be incorporated to enable continuous cardiac health monitoring.
Additionally, advanced feature selection techniques and attention-based models may further enhance classification accuracy while reducing computational complexity.

Finally, clinical validation in collaboration with healthcare professionals is necessary to evaluate the system's applicability in real-world diagnostic environments and to ensure medical reliability.

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REFERENCES

[1] U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J. Tan, and M. Adam, "Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network," Information Sciences, vol. 405, pp. 81–90, 2017.

[2] P. Rajpurkar et al., "Cardiologist-level arrhythmia detection with convolutional neural networks," Nature Medicine, vol. 25, no. 1, pp. 65–69, 2019.

[3] M. Llamedo and J. P. Martínez, "Heartbeat classification using feature selection driven by database generalization criteria," IEEE Transactions on Biomedical Engineering, vol. 58, no. 3, pp. 616–625, 2011.

[4] I. H. Witten, E. Frank, M. A. Hall, and C. J. Pal, Data Mining: Practical Machine Learning Tools and Techniques, 4th ed. Burlington, MA, USA: Morgan Kaufmann, 2016.

[5] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining, 2016, pp. 785–794.

[6] C. Cortes and V. Vapnik, "Support-vector networks," Machine Learning, vol. 20, no. 3, pp. 273–297, 1995.

[7] L. Breiman, "Random forests," Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.

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