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Detection of Cardiovascular Diseases in ECG Images using Deep Learning Techniques

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Abstract: This paper presents an intelligent system for automated ECG image classification, aiming to support the early and accurate detection of cardiovascular diseases (CVDs), the leading global cause of death. The system distinguishes four cardiac conditions: normal rhythm, abnormal rhythm, acute myocardial infarction (MI), and prior MI. It employs a two-stage approach combining deep learning and classical machine learning. Convolutional Neural Network, SqueezeNet, AlexNet, Xception extract high-level features via transfer learning, which are then classified using traditional algorithms. A lightweight web application, built with Flask and SQLite, enables secure user access and ECG analysis. Results highlight the effectiveness of this hybrid framework in enhancing diagnostic accuracy and clinical support.
Keywords: Cardiovascular Diseases (CVD), Electrocardiogram (ECG), Deep Learning, Transfer Learning, Convolutional Neural Network (CNN), SqueezeNet, AlexNet, Xception, Machine Learning, Feature Extraction, Flask.

I. INTRODUCTION

Cardiovascular diseases (CVDs) account for the highest number of deaths globally, emphasizing the need for fast and reliable diagnostic solutions. Among available tools, electrocardiograms (ECGs) are widely adopted due to their affordability, non-invasiveness, and real-time monitoring capabilities. Yet, conventional ECG analysis often depends on manual interpretation, which can be inconsistent and inefficient, particularly in strained healthcare settings. This paper introduces an automated system that applies deep learning and machine learning techniques to ECG image data, aiming to boost diagnostic precision, minimize evaluation delays, and provide scalable support for real-time clinical use.

A. Objective

To improve early detection of heart conditions, an AI-based method is applied to interpret ECG images automatically. The system identifies patterns using advanced learning techniques and classifies heart abnormalities with improved speed and consistency. By adapting existing knowledge through transfer learning, it minimizes training requirements. A user-friendly web interface allows secure access, image uploads, and quick diagnostic results, offering practical support for timely cardiovascular evaluation.

II. LITERATURE SURVEY

Artificial intelligence (AI) has increasingly become central to improving the analysis of electrocardiogram (ECG) signals, especially in the context of early detection and diagnosis of cardiovascular diseases (CVDs), which remain the top cause of mortality worldwide. The ability of AI to automate ECG interpretation holds significant promise in enhancing clinical accuracy and efficiency. This survey presents a critical review of recent research in AI-based ECG classification, focusing on different techniques and their practical relevance in healthcare settings.

Dissanayake et al. (2021) investigated how different feature selection methods influence classification performance. Utilizing the Cleveland heart disease dataset, they evaluated a wide range of selection techniques and classifiers. Their results showed that backward feature elimination, paired with decision tree algorithms, achieved the highest accuracy. This study underscores the importance of selecting relevant features when building interpretable and high-performing predictive models [1].

In a different but related context, Ozcan (2021) introduced a composite framework for detecting COVID-19 from chest X-ray images using both shallow and deep feature extraction. Although focused on a different imaging modality, the dual-model structure—designed for both binary and multiclass tasks—can be adapted for ECG classification problems. The study illustrates how methodologies from other medical domains can inform and enrich cardiovascular AI applications [2].

Khan et al. (2021) implemented a deep learning system to classify multiple cardiac conditions using 12-lead ECG images. The model was designed for efficiency and achieved strong diagnostic performance while maintaining a compact architecture.

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The results, validated by medical professionals, suggest its suitability for deployment in both clinical settings and mobile health platforms where computational efficiency is essential [3]. Nannavecchia et al. (2021) proposed a lightweight 1D Convolutional Neural Network (1D-CNN) model tailored for real-time detection of multiple cardiac anomalies. Designed with computational efficiency in mind, the model is suitable for integration into portable health monitoring devices, offering a promising solution for continuous personal heart health tracking in smart healthcare applications [4].

Bharti et al. (2021) explored a hybrid predictive approach by combining traditional machine learning and deep learning methods to diagnose heart disease using the UCI dataset. Their model utilized Isolation Forest for feature selection and normalization techniques to enhance data quality, resulting in improved prediction accuracy. The study highlights the potential of integrated ML-DL frameworks in optimizing diagnostic performance [5].

III.METHODOLOGY OF THE PROPOSED SYSTEM

A. Proposed System

The proposed AI-based ECG Diagnostic System surpasses traditional approaches by offering an integrated, image-driven, and web-accessible solution for cardiac abnormality detection. Unlike manual interpretation or rigid rule-based systems, it uses deep learning and transfer learning to extract meaningful features from ECG images, enabling accurate diagnosis even with limited data. Unlike tools limited to offline use or specific input formats, this system supports real-time predictions via a user-friendly web interface with secure login and image upload functionality. By combining automated feature extraction with machine learning classifiers, the system improves diagnostic precision while reducing reliance on manual effort. Unlike fragmented solutions that require multiple tools or user intervention, it delivers end-to-end automation—from ECG image input to prediction output—within a single platform. Its scalable, lightweight design also makes it suitable for deployment in both clinical and low-resource settings, ensuring broad accessibility and practical utility.

B. System Architecture

The AI-Based ECG Classification System architecture can be explained as follows:

1) Input Layer: Accepts ECG images from the dataset, serving as the primary data source for downstream processing.
2) Feature Extraction Layer: Utilizes deep learning techniques to extract relevant features from ECG images. This includes multiple CNN-based architectures tailored for capturing spatial and temporal patterns.
3) Machine Learning Classification Layer: Processes extracted features using traditional machine learning algorithms such as Random Forest, SVM, KNN, Decision Tree, and Naïve Bayes to classify cardiac conditions.
4) Performance Evaluation Layer: Assesses the effectiveness of the classification using key metrics including Accuracy, Precision, Recall, and F1-score, ensuring reliable model performance.
5) Output Layer: Delivers the final prediction indicating the type of cardiac abnormality detected, providing actionable insights for further clinical interpretation.

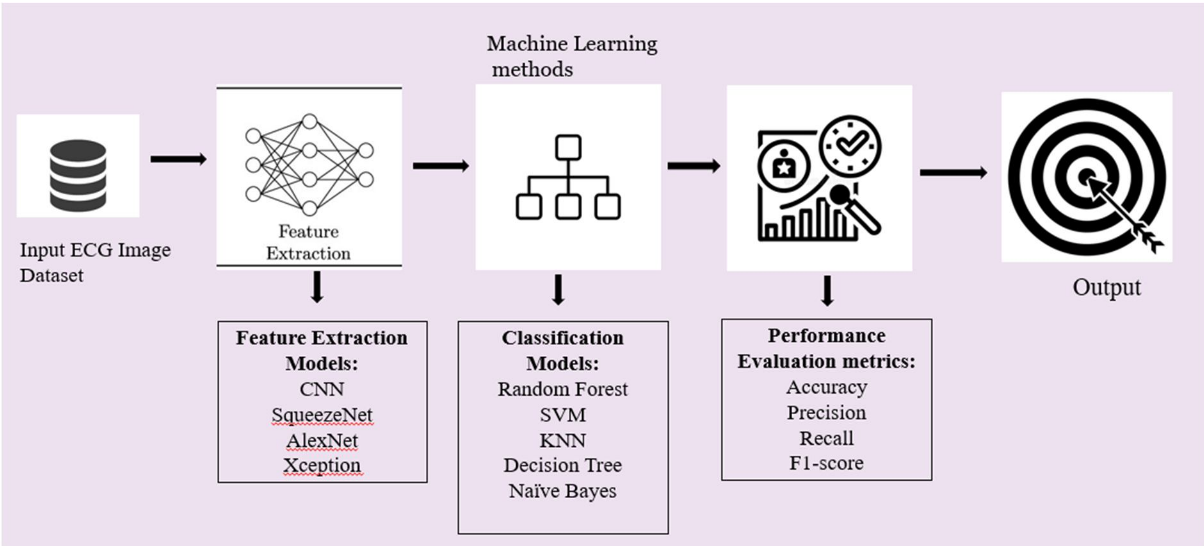

Fig 1: System Architecture

C. Methodology

The methodology section outlines the plan and method that shows how the project is organized and implemented:

1) ECG Image Acquisition and Preprocessing: This module involves collecting ECG images representing four different cardiac classes: Normal, Myocardial Infarction, History of MI, and Abnormal Heartbeat. The images are first resized to a standard resolution (128×128 pixels) to maintain consistency across the dataset. Preprocessing steps include normalization of pixel values to a [0,1] range and encoding of class labels using one-hot encoding. The TensorFlow ImageDataGenerator is used to split the data into training, validation, and test sets, while also enabling batch processing and augmentation where necessary.
2) End-to-End Deep Learning Classification: In this module, a direct approach to ECG classification is implemented using convolutional neural networks (CNNs). The processed ECG images are fed into deep learning architectures that learn hierarchical features for classification. Training is done using categorical cross-entropy loss with the Adam optimizer. To prevent overfitting, callbacks such as EarlyStopping and ReduceLROnPlateau are applied. Each model is trained up to 200 epochs with performance tracked via accuracy, precision, recall, and F1-score.
3) Hybrid Deep Learning + Machine Learning Model: This component focuses on combining deep feature extraction with traditional classifiers. Features are extracted from the fully connected layers of pre-trained deep models. These high-dimensional vectors are then input into machine learning classifiers such as Support Vector Machine (SVM), Random Forest, K-Nearest Neighbors (KNN), Decision Tree, and Naive Bayes. This modular approach helps in understanding the separability of learned features and offers more interpretable decision boundaries.
4) Performance Evaluation and Comparison: This module involves assessing the performance of both end-to-end and hybrid models using key metrics such as accuracy, precision, recall, F1-score, and confusion matrix. Training and validation accuracy are monitored over epochs, and each model's performance is compared to identify the best-performing strategy. Feature-based models are additionally evaluated for their computational efficiency and robustness across varying datasets.
5) Web Application Deployment: A Flask-based web interface is developed for deploying the trained model in a user-accessible format. The application includes user authentication, ECG image upload functionality, and a results dashboard that displays predicted class labels and confidence scores. The system architecture ensures that backend model inference is seamlessly integrated with frontend components for a smooth user experience.

IV. IMPLEMENTATION AND RESULTS

The ECG classification system includes the following core features:

1) Web-Based User Interface: A secure Flask application enables users to log in, upload ECG images, and receive instant predictions.
2) Efficient Deep Learning Architecture: The final model uses a lightweight SqueezeNet architecture for end-to-end ECG classification, ensuring high speed and accuracy with minimal complexity.
3) Hybrid Model Benchmarking: Deep features were also evaluated using traditional ML classifiers like Random Forest and Decision Trees to validate feature quality.
4) Streamlined Deployment: The complete model is packaged in a single .h5 file, simplifying integration and future updates.
5) Optimized Training Strategy: EarlyStopping and learning rate reduction callbacks ensured fast convergence and prevented overfitting.
6) Thorough Evaluation Metrics: Accuracy, precision, recall, and F1-score were computed across four ECG classes to confirm model reliability.

S.No.	ML Model	Accuracy	Precision	Recall	F1_score
0	SqueezeNet	1.000	1.000	1.000	1.000
1	AlexNet	0.995	1.000	0.990	0.995
2	CNN	0.743	0.747	0.742	0.745
3	Xecption	0.995	0.995	0.995	0.995
4	Xecption - RF	1.000	1.000	1.000	1.000

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S.No.	ML Model	Accuracy	Precision	Recall	F1_score
5	Xecption - SVM	0.459	0.421	0.459	0.403
6	Xecption - KNN	0.896	0.899	0.896	0.892
7	Xecption - DT	1.000	1.000	1.000	1.000
8	Xecption - NB	0.444	0.421	0.444	0.411
9	CNN - RF	1.000	1.000	1.000	1.000
10	CNN - SVM	0.370	0.232	0.370	0.259
11	CNN - KNN	0.858	0.862	0.858	0.850
12	CNN - RF	1.000	1.000	1.000	1.000
13	CNN - NB	1.000	1.000	1.000	1.000
14	AlexNet - RF	1.000	1.000	1.000	1.000
15	AlexNet - SVM	0.317	0.257	0.317	0.169
16	AlexNet - KNN	0.861	0.865	0.861	0.850
17	AlexNet - DT	1.000	1.000	1.000	1.000
18	AlexNet - NB	0.420	0.513	0.420	0.352
19	SqueezeNet - RF	0.998	0.998	0.998	0.998
20	SqueezeNet - SVM	0.346	0.305	0.346	0.215
21	SqueezeNet - KNN	0.927	0.928	0.927	0.925
22	SqueezeNet - DT	0.994	0.994	0.994	0.994
23	SqueezeNet - NB	0.525	0.504	0.525	0.503
24	CNN -DT	1.000	1.000	1.000	1.000

Table 1: Performance Comparison Table

A. Results

The ECG classification system was evaluated on four categories: Abnormal, HMI, MI, and Normal. Among various models tested, SqueezeNet achieved 100% accuracy, precision, recall, and F1-score, outperforming other architectures like AlexNet and Xception.
Hybrid models using CNN features with Random Forest and Decision Tree also delivered strong results, confirming the quality of extracted features. However, SqueezeNet was chosen for deployment due to its lightweight design, faster inference, and ease of integration.
Training was optimized using callbacks like EarlyStopping and ReduceLROnPlateau, ensuring high generalizability and preventing overfitting. The final model, stored as a single .h5 file, was integrated into a Flask-based web application, delivering real-time predictions with minimal computational load.

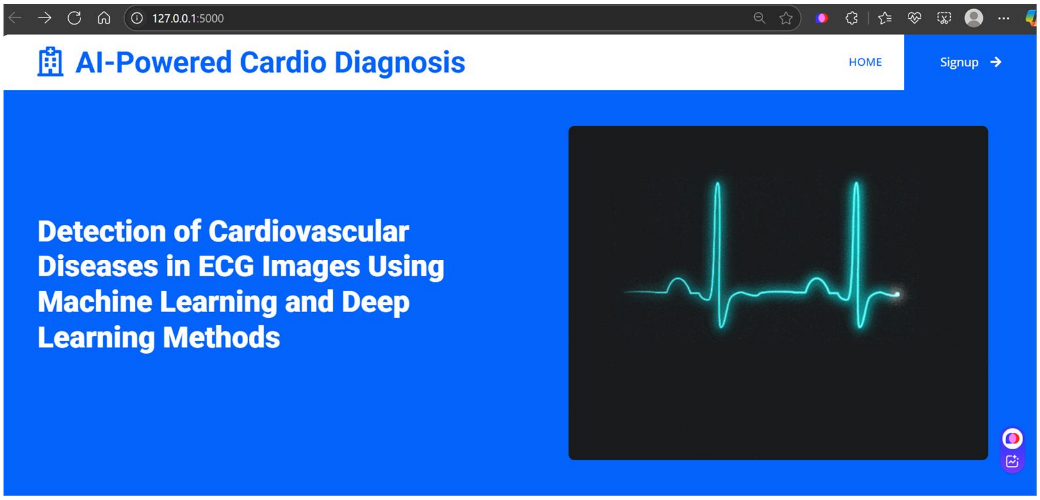

Fig 2: Home Page

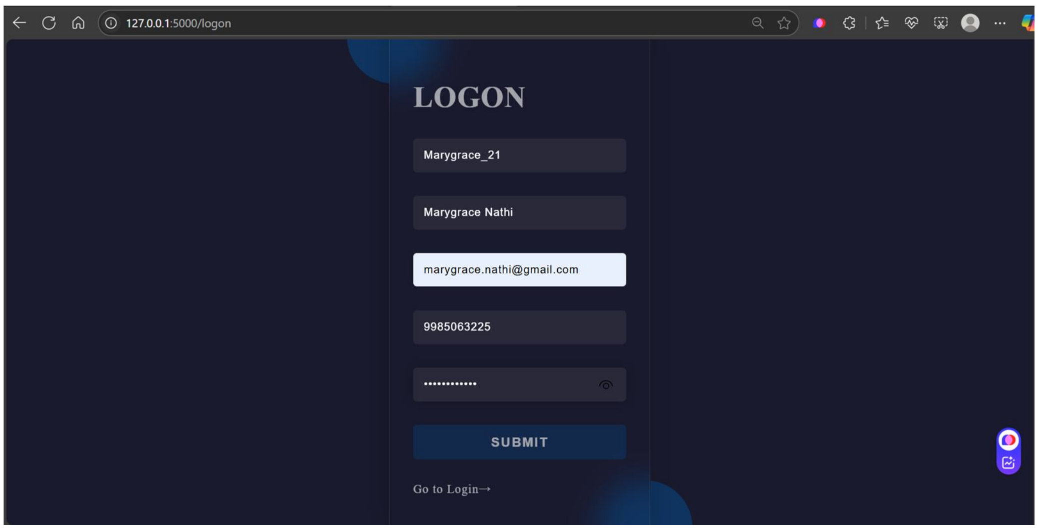

Fig 3: Sign Up Page

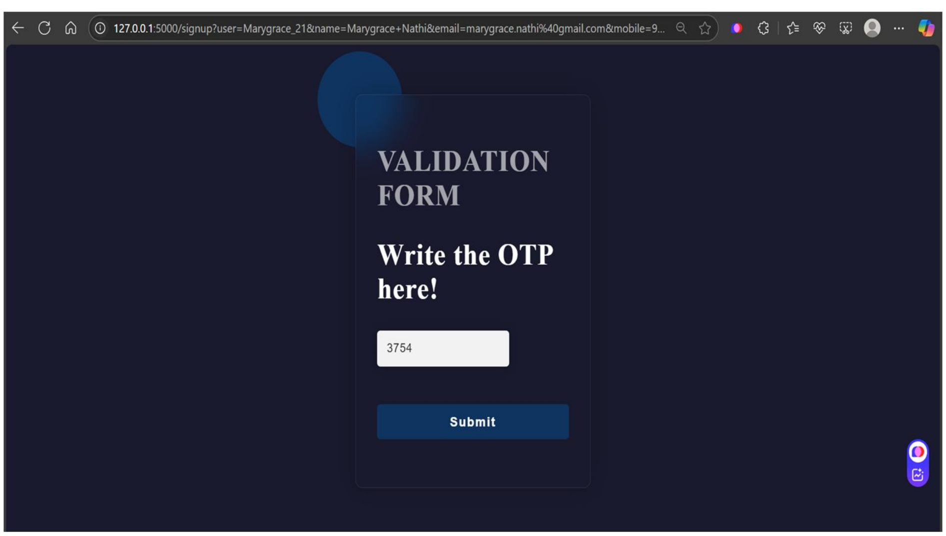

Fig 4: OTP Validation Page

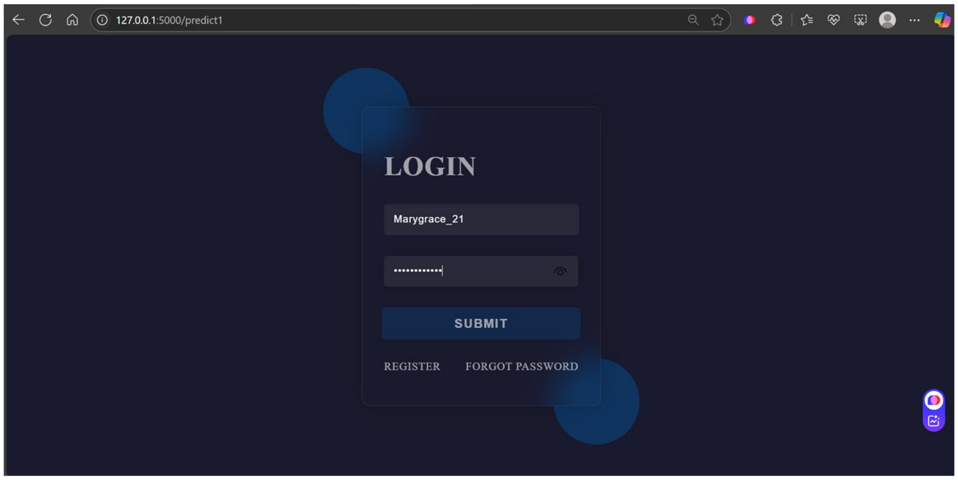

Fig 5: Log in Page

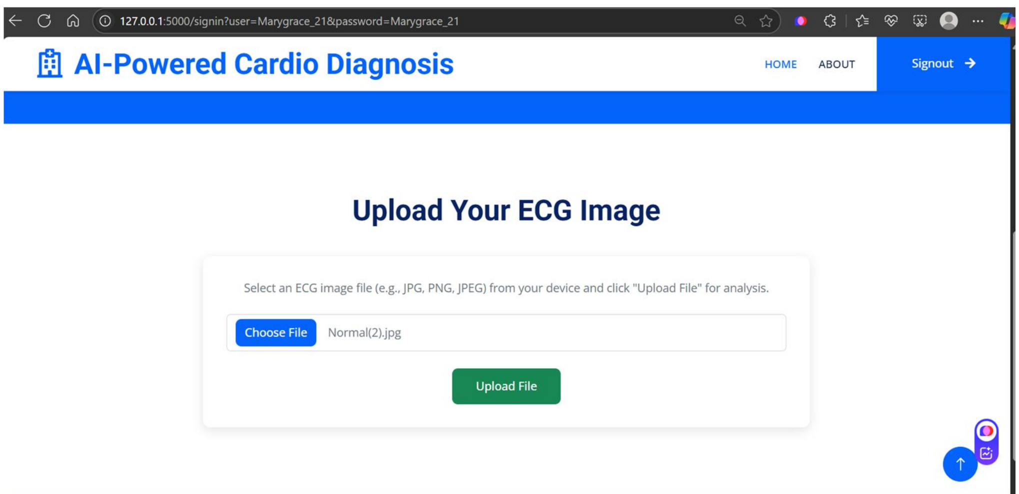

Fig 6: Prediction Page

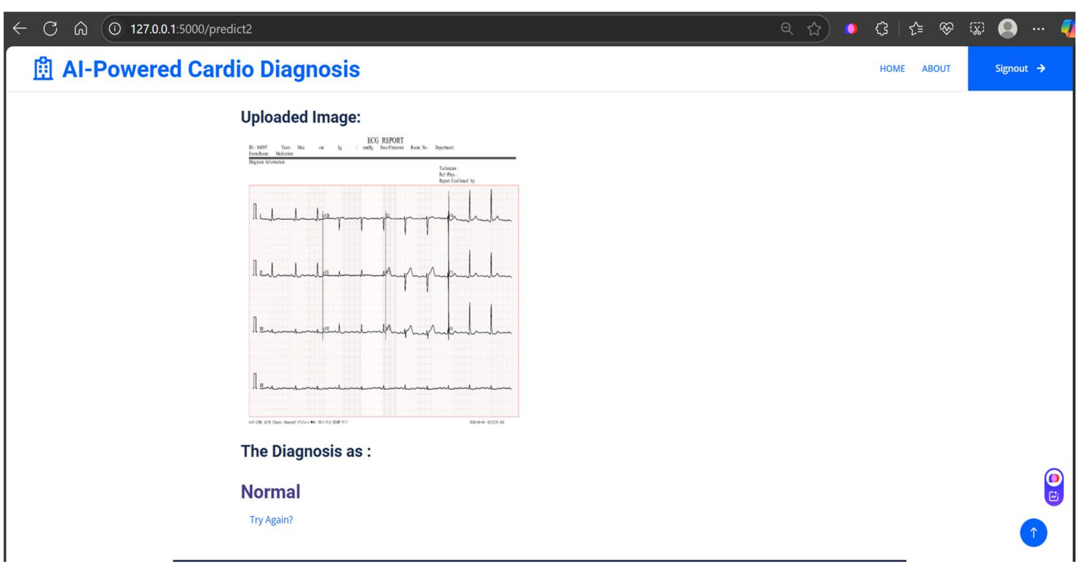

Fig 7: Result Page

V. LIMITATIONS AND FUTURE SCOPE

The ECG classification system, while effective, has limitations. It was trained on a specific dataset, so its generalizability to diverse clinical data remains untested. It also depends on high-quality ECG images and only classifies four cardiac conditions, excluding others. Additionally, it processes static images, lacking real-time signal analysis.

Future work includes expanding the dataset for broader validation, adding noise reduction techniques, and supporting more cardiac classes. Integrating explainable AI for interpretability, optimizing for mobile deployment, and enabling real-time ECG signal analysis would enhance the system's usability and clinical impact.

VI. CONCLUSION

This research demonstrates the feasibility and effectiveness of deep learning-based ECG classification for accurate cardiac diagnosis. The proposed system delivers high accuracy, real-time performance, and easy deployment through a web interface, making it a practical tool for clinical and remote healthcare use. By combining precision with accessibility, this work contributes meaningfully to early cardiac disorder detection and paves the way for scalable, AI-assisted diagnostic solutions.

VII. ACKNOWLEDGMENT

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