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Real - Time Recognition of Cardiovascular Conditions from ECG Images with Deep Learning

Kondeti Sai Likhitha[1]; Pathakamudi Jahnavi[2]; Manchala Siddhardha[3];
Sri. Chekka Ratna Babu[4]

[1,2,3] B. Tech. Student, Dept. of Computer Science and Engineering, R.V.R. & J.C. College of Engineering, Chowdavaram, Guntur, Andhra Pradesh, India
[4] Associate Professor, Dept. of Computer Science and Engineering, R.V.R. & J.C. College of Engineering, Chowdavaram, Guntur, Andhra Pradesh, India

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Abstract: Cardiovascular disease (CVD) remains the leading cause of mortality globally. This study proposes a deep learning-based framework for the detection of cardiovascular conditions from electrocardiogram (ECG) images. Three architectures AlexNet, SqueezeNet, and a custom-designed Convolutional Neural Network (CNN) were trained and evaluated, achieving classification accuracies of 88%, 81%, and 100%, respectively. To facilitate real-world applicability, the models were deployed via a web application using Streamlit, enabling real-time prediction from uploaded ECG images. Furthermore, a majority voting scheme was employed to enhance prediction reliability. The proposed system demonstrates the potential of deep learning models in aiding cardiovascular diagnosis and emphasizes the importance of accessible deployment tools. Future research will focus on larger datasets, additional cardiac conditions, and model interpretability through explainable AI techniques.

➢ ***Impact Statement***

Artificial intelligence (AI) continues to transform the field of healthcare, particularly in enhancing early detection and diagnosis of life-threatening diseases. In this work, an automated system for the detection of cardiovascular diseases from ECG images has been developed using deep learning methods, including AlexNet, SqueezeNet, and a custom-designed CNN. The proposed models achieved remarkable classification accuracy, with the custom CNN attaining 100% accuracy on the testing dataset. Importantly, the lightweight architectures are optimized to operate efficiently on systems with limited computational resources, enabling real-time deployment on standard CPUs without the need for high-end GPUs. Furthermore, ensemble techniques such as majority voting have been incorporated to enhance prediction reliability. This advancement has the potential to assist clinicians by providing quick, accurate, and scalable diagnostic support, ultimately contributing to earlier intervention and improved patient outcomes.

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I. INTRODUCTION

Cardiovascular diseases (cvds) are among the leading causes of death globally, responsible for approximately 17.9 million deaths annually, as reported by the World Health Organization (who). Detecting and addressing health issues at an early stage and taking prompt action are essential in minimizing mortality rates and enhancing patient outcomes. Electrocardiography (ecg) is a commonly used, non-invasive, and affordable diagnostic tool for identifying heart abnormalities

In recent times, the emergence of deep learning techniques has brought about a significant transformation in the field of medical imaging, providing promising solutions for automating disease detection with exceptional accuracy. Deep learning models have the ability to learn intricate patterns directly from raw data, eliminating the need for manual feature extraction, which makes them highly effective in analyzing ecg images. This research concentrates on the creation of a machine learning-based system that can automatically identify cardiovascular diseases from electrocardiogram (ecg) images. Three different deep learning architectures — alexnet, squeezenet, and a custom-designed convolutional neural network (cnn) — were trained and evaluated on a dataset comprising four categories: myocardial infarction (mi) patients, patients with a history of mi, abnormal heartbeats, and normal ecgs. The well-trained models demonstrated remarkable classification accuracy, with the custom CNN model achieving an outstanding accuracy of

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100% on the testing dataset.

To bridge the gap between research and clinical applicability, the trained models were deployed through a user-friendly web application built with streamlit, allowing real-time predictions on new ecg images. Additionally, a majority voting approach was implemented to strengthen the system's reliability by combining the advantages of various models.

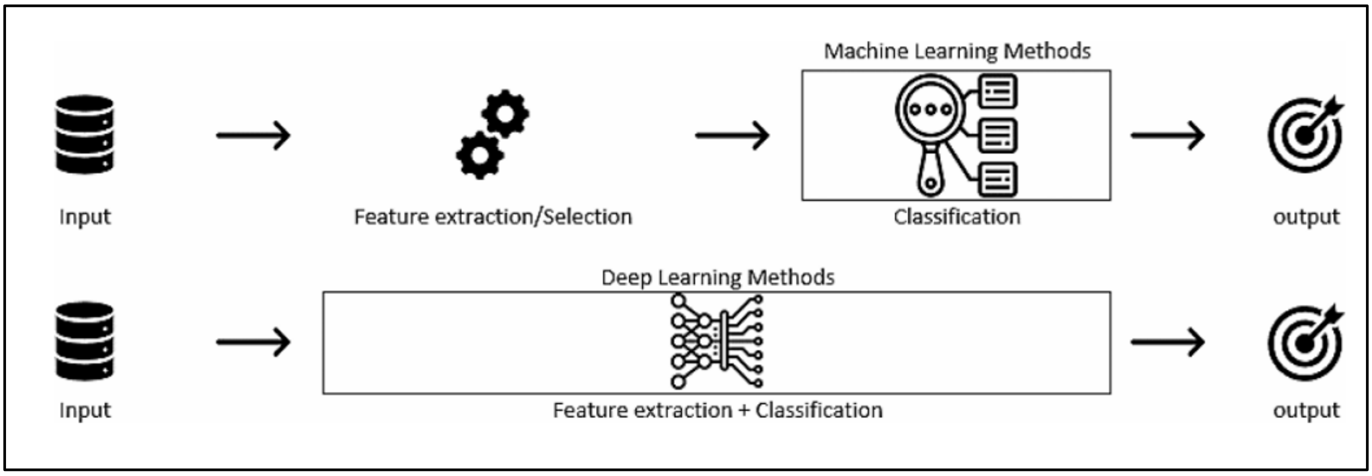

Fig 1 Machine Learning and Deep Learning Abstract Concepts

➢ *The Contributions of this work are Threefold:*

- Development and comparison of three deep learning models for ECG-based cardiovascular disease detection.
- Deployment of the models using a Streamlit-based web application for real-time predictions.
- Implementation of a majority voting mechanism to improve prediction reliability and reduce individual model biases.

II. LITERATURE REVIEW

Cardiovascular disease (cvd) continues to be a major cause of death globally, underscoring the significance of identifying and addressing the condition at an early stage. Throughout the years, various computational methods have been suggested for analyzing electrocardiogram (ecg) data, aiming to provide timely and accurate diagnoses. In the early stages of ecg classification research, traditional machine learning methods like support vector machines (svm), k-nearest neighbors (k-nn), and random forests were extensively employed. However, these methods often require manual feature extraction and domain expertise, limiting scalability and generalizability across all the datasets. Thanks to the progress in deep learning, convolutional neural networks (cnns) have gained popularity because they can automatically identify important features in raw images.

In Acharya et al. [1], 2017, a CNN-based architecture was proposed to classify arrhythmias using ECG signals, demonstrating superior performance over traditional classifiers. Similarly, Kiranyaz et al [2]. Introduced a 1D CNN model for patient-specific arrhythmia detection, showcasing robust real-time capabilities. Recent research has shifted focus toward applying 2D CNNs to ECG image data, transforming ECG signals into visual representations for image-based classification. AlexNet and its derivatives, such as SqueezeNet and ResNet, have shown promising results when adapted for biomedical image classification tasks due to their strong feature extraction capabilities.

Lightweight models like MobileNet and SqueezeNet have also been explored to facilitate deployment on edge devices and resource-constrained environments. These models trade off minor reductions in accuracy for significantly improved inference time and reduced memory consumption. Despite these advancements, there remains a gap in combining model accuracy, computational efficiency, and deployability. Therefore, there is a growing need to explore hybrid and ensemble techniques, model compression, and deployment strategies that can ensure real-time, accurate ECG classification for clinical use.

This study builds upon prior work by comparing multiple CNN-based models including AlexNet, SqueezeNet, and a custom CNN, and aims to deploy them via a user-friendly Streamlit interface for real-world usability.Talo [4] presented a method using RR interval signals and deep neural networks for heartbeat classification, emphasizing the role of temporal signal features. Their work highlighted the usefulness of non-image-based ECG signal features in detecting heart abnormalities.

Yildirim [5] used a combination of wavelet transforms and a Bi-directional Long Short-Term Memory (BiLSTM) network for ECG signal classification. Their hybrid method captured both spatial and temporal features, improving the overall model performance on multiple arrhythmia classes. Islam et al. [6] applied traditional machine learning classifiers to predict cardiovascular risk using demographic and ECG-derived features. While not as accurate as deep learning methods, their work emphasized the role of feature

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engineering and ensemble techniques. Recent work by Li et al. [7] focused on deploying lightweight CNNs for edge devices, addressing the challenge of computational limitations in rural or mobile healthcare applications. Their approach was able to classify ECGs efficiently on CPUs without sacrificing much accuracy.

More recent studies like Zhang et al. [8] explored attention mechanisms in deep learning models to focus on critical waveforms like QRS complexes and P-T intervals. These attention-based methods increased interpretability and performance.

III. METHODS

- *Pretrained Deep Learning Models*

Pretrained deep learning models, such as AlexNet and SqueezeNet, have proven effective for tasks like ECG image classification through the use of transfer learning and feature extraction. These models, originally trained on large-scale datasets like ImageNet, possess rich feature representations that can be repurposed for medical image analysis. In transfer learning, the final layers of these models are replaced with new layers tailored to the target task—in this case, classifying ECG images into specific cardiovascular conditions—while retaining the convolutional base to leverage learned low- and mid-level features. Fine-tuning these modified models on the ECG dataset allows them to adapt to the domain-specific patterns present in the signals. Additionally, pretrained networks can be used as fixed feature extractors by removing the classifier head and using the output of intermediate layers as input to traditional machine learning algorithms. This approach is particularly beneficial when working with limited computational resources or datasets, as it significantly reduces training time and improves model accuracy. In this study, AlexNet and SqueezeNet demonstrated high efficiency and accuracy in detecting cardiovascular diseases, with both models being lightweight enough to run on standard CPUs, making them practical for real-world healthcare applications.

- *Proposed Cnn Architecture*

In the field of deep learning, convolutional neural networks (cnns) are a specific type of deep neural networks that are primarily used for image classification and analysis purposes. The computer system processes input data in three dimensions, considering height, width, and depth (or channels). For example, an input image with dimensions 227 × 227 × 3 represents a width and height of 227 pixels each and three color channels (typically rgb). The primary goal of a CNN is to automatically identify and extract important and unique characteristics from the input images using a hierarchical structure.

The fundamental components of CNNs are pooling layers and convolutional layers. Convolutional layers perform an essential task of feature extraction by applying filters (also called as kernels) over the input image. These filters slide across the input spatially, performing element wise multiplication and summing the results to produce the feature maps which highlights specific patterns such as edges, textures, or shapes. Since the convolution operation is inherently linear, it is typically followed by a non-linear activation function relu (rectified linear unit) or its variants to introduce non-linearity, enabling the network to learn complex mappings.Following the convolutional layers, pooling layers—such as max-pooling—are employed to reduce the spatial dimensions of the feature maps. This downsampling process helps to extract the most salient features while reducing computational complexity. This process, known as down sampling, decreases the number of parameters and computations in the network while also helping to make the features more invariant to small translations in the input. Toward the end of the network, fully connected layers integrate the extracted features for the final decision-making, and the last layer typically uses a softmax or sigmoid activation function to output class probabilities. This structured architecture enables cnns to effectively learn spatial hierarchies of features, making them highly effective for tasks such as ecg image classification.

The proposed convolutional neural network (cnn) architecture has a total of 38 layers, including three max-pooling layers, eight leaky relu activation layers, eight batch normalization layers, five dropout layers, six 2d convolutional layers, three fully connected layers, two depth concatenation layers, and a final soft max output layer. This structure is created to extract the most important features from ecg images, which can then be used to enhance the accuracy of classification.

The architecture is composed of two parallel branches—referred to as the stack branch and full branch—which process the input image simultaneously to enhance the feature learning. The input to the model is an ecg image with dimensions of 227 × 227 × 3, and both branches commence processing from this shared input. Within the stack branch, the model utilizes three sequential 2d convolutional layers, each with a kernel size of 3 × 3. Each convolutional layer is immediately followed by a leaky relu activation layer, a batch normalization layer, and a max-pooling layer.

The leaky relu activation function, with a negative slope coefficient of 0.1, is chosen over standard relu to prevent the "dying relu" situation by allowing a small gradient when the unit is not active. The batch normalization layers standardize the inputs to each mini-batch, improving the training overall stability and speed of the model. Max-pooling layers, with a 6 × 6 filter with a stride of 3, are used to down sample feature maps, which reduces the spatial dimensions, lowers the number of parameters, and decreases the computational burden. This carefully designed configuration enables the model to effectively learn hierarchical features from the ecg images while addressing issues like vanishing gradients and overfitting, ultimately enhancing the model's classification

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accuracy and efficiency. The suggested CNN model incorporates max-pooling layers with a filter size of 6x6 and a stride of 3. In this section, 64, 128, and 224 filters are employed to extract intricate details from the data for the initial, second, and third convolutional layers, respectively. The output size of the full branch of our proposed cnn model is 2 × 2 × 224. The first layer in this branch is a fully connected layer, which is why it is referred to as such. In our model, the fully connected layer consists of 16 neurons.

Each neuron in a fully connected layer is connected to each neuron in the previous layer. This is different from a neuron in a convolutional layer, which is linked to a specific number of neurons in the previous layer based on the size of the convolutional filter. While the majority of the parameters in the CNN are derived from the fully connected layers, the convolutional layer necessitates a significantly larger amount of memory for calculations. After the fully connected layer, there is a leakyrelu layer, a batch normalization layer, and a dropout layer, which work together to prevent overfitting and enhance the model's ability to generalize. The two convolutional layers, named conv04 and conv05, are positioned at the same level after the block of the fully connected layer to aid in the extraction of more comprehensive features.

Conv04 is a convolutional layer of 322x2 with a stride of 1 and padding of 1, whereas conv05 is a convolutional layer of 64 3x3 with a stride of 2 and padding of 2. The feature maps generated by the 2 convolutional layers are combined to create a feature map with dimensions of 2×2×96. To prevent overfitting and account for correlated features, a dropout layer is then applied. The two outputs produced by the two branches are combined to form a feature map with dimensions of 2×2×320. After that, a dropout layer is introduced to minimize the overfitting of the model. To enhance the nonlinearity of the model and decrease the number of feature maps, a 1×1 convolutional layer with 256 filters is incorporated. To enhance the classification process, a layer consisting of 512 neurons is incorporated into the fully connected layer.

The output consists of a fully connected layer with 4 neurons, each representing a class to be classified, followed by a soft max layer to determine the predicted output.

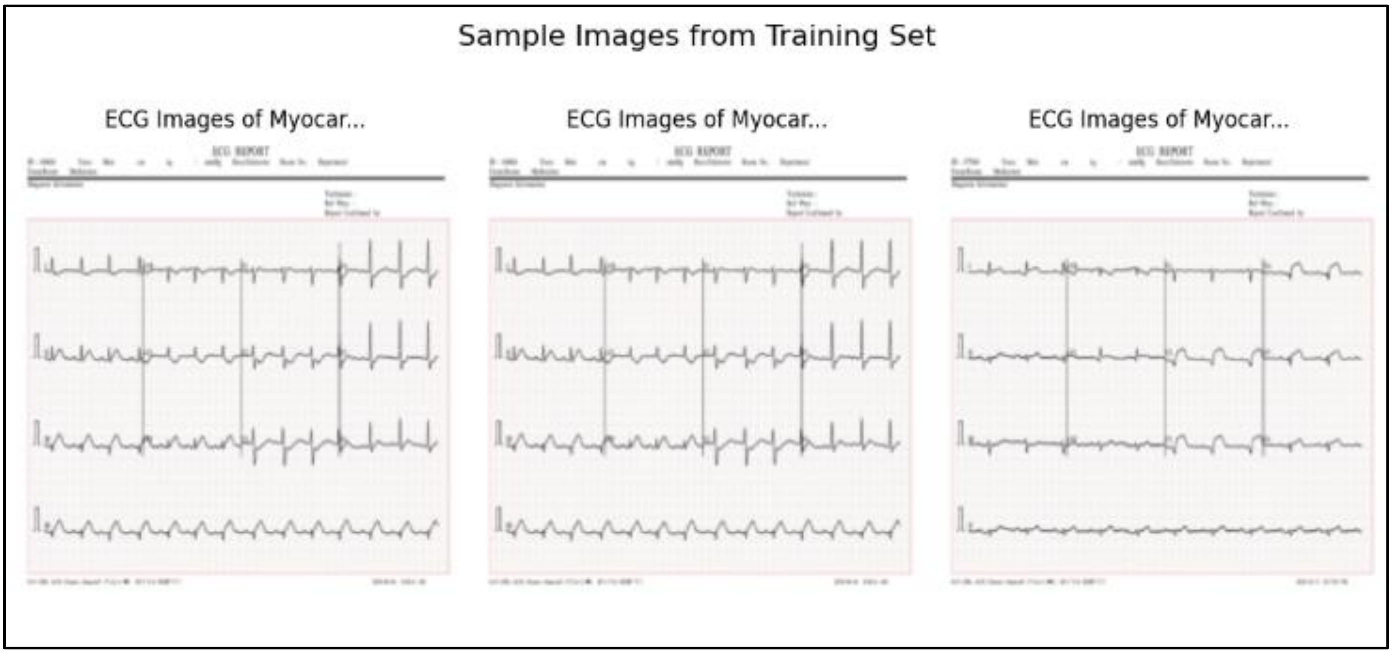

Fig 2 Sample Images from Training Set

IV. IMPLEMENTATION DETAILS

➢ *Dataset Description*

The dataset used consists of ECG images collected from multiple patients, categorized into four classes: Myocardial Infarction (MI) Patients, History of MI, Abnormal Heartbeat, and Normal ECG. The dataset was split into training, validation, and testing sets to evaluate the model performance effectively. Each image was resized to a consistent shape of 227×227×3 to match the input requirements of the models used.

➢ *Preprocessing*

Before feeding the images into the neural networks, several preprocessing steps were applied. Images were resized to 227×227 pixels and normalized to have zero mean and unit variance using standard normalization techniques. Data augmentation methods such as random rotation and horizontal flipping were also used to improve generalization and reduce overfitting.

➢ *Model Training And Evaluation*

Three deep learning architectures were trained and evaluated: AlexNet, SqueezeNet, and a custom-designed

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CNN. Transfer learning was applied to AlexNet and SqueezeNet by modifying the final layers to fit the four output classes. The models were trained using the Adam optimizer with a categorical cross-entropy loss function. Model training was performed on a standard CPU-based machine with PyTorch as the backend.

AlexNet achieved an accuracy of 88%, SqueezeNet achieved an accuracy of 81%, Custom CNN achieved an accuracy of 100% on the test set.

To further enhance reliability, a majority voting ensemble strategy was used to combine predictions from all three models and generate a final prediction.

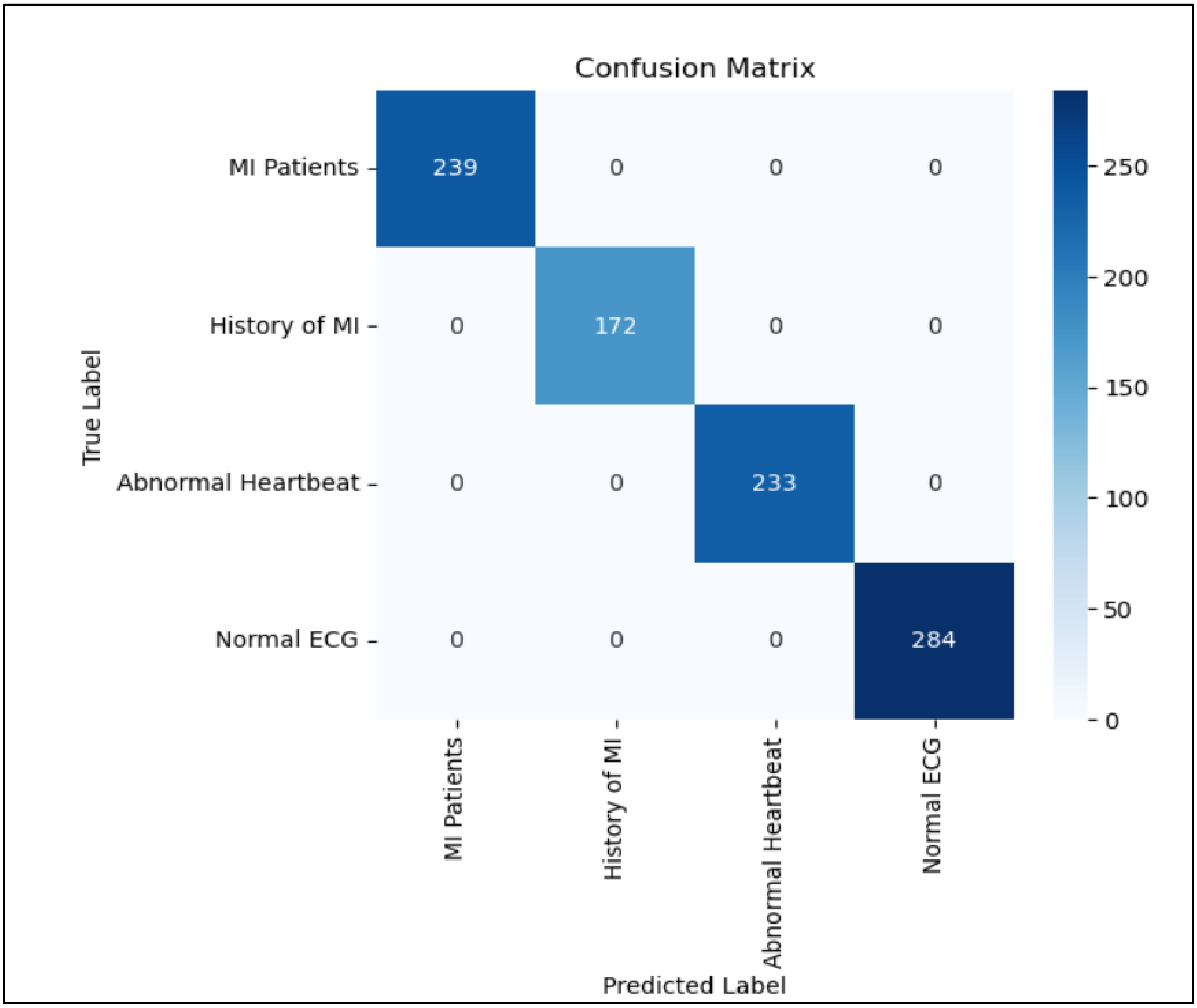

Fig 3 Confusion Matrix of the Custom CNN

➢ *Deployment Using Streamlit*

To demonstrate the practicality and accessibility of the proposed cardiovascular disease detection system, the final model ensemble—comprising alexnet, squeezenet, and a custom cnn architecture—was deployed using streamlit, a lightweight and efficient python-based web application framework. Streamlit enables the development of interactive web interfaces directly from Python scripts, making it a perfect tool for quickly deploying machine learning models. The deployed system allows users, such as healthcare professionals and researchers, to easily upload ecg images using a user-friendly graphical interface and obtain instant predictions about possible cardiovascular issues. This deployment not only improves the usability of the model but also connects technical innovation with real-world medical application, making it accessible to individuals without a technical background. Furthermore, the web application is compatible with popular image formats (e.g., jpg, jpeg, png) and is designed to minimize latency during inference, making it a suitable choice for clinical and remote health monitoring applications.

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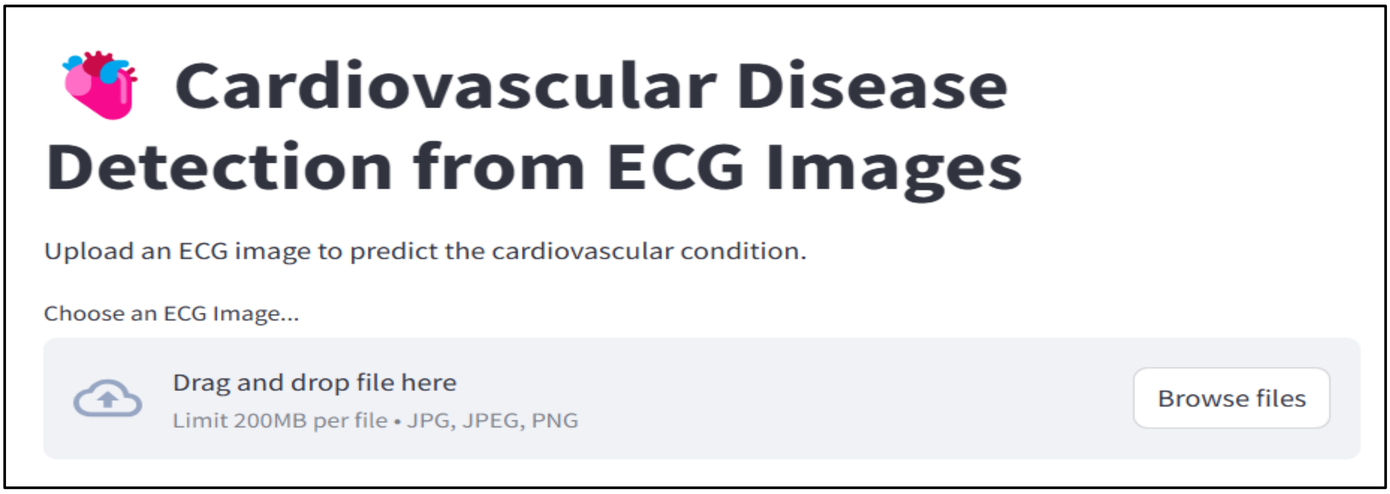

Fig 4 Streamlet-Based user Interface for Cardiovascular Disease Detection from ECG Images, Allowing Users to Upload and Analyze ECG Scans for Real-Time Classification.

The app enables users to capture ecg images using a user friendly interface, processes them instantly, and presents the predicted cardiovascular condition. Each model provides a prediction, and the most frequently occurring prediction is chosen as the final outcome through a voting process. This deployment is highly efficient on the CPU, making it well-suited for practical use in low-resource settings like rural clinics or mobile diagnostic units. The system's intuitive design eliminates the need for advanced technical knowledge, making it accessible to a wider range of users. Additionally, the combination of ensemble predictions strengthens diagnostic reliability, offering a dependable and scalable approach for early detection of cardiovascular diseases.

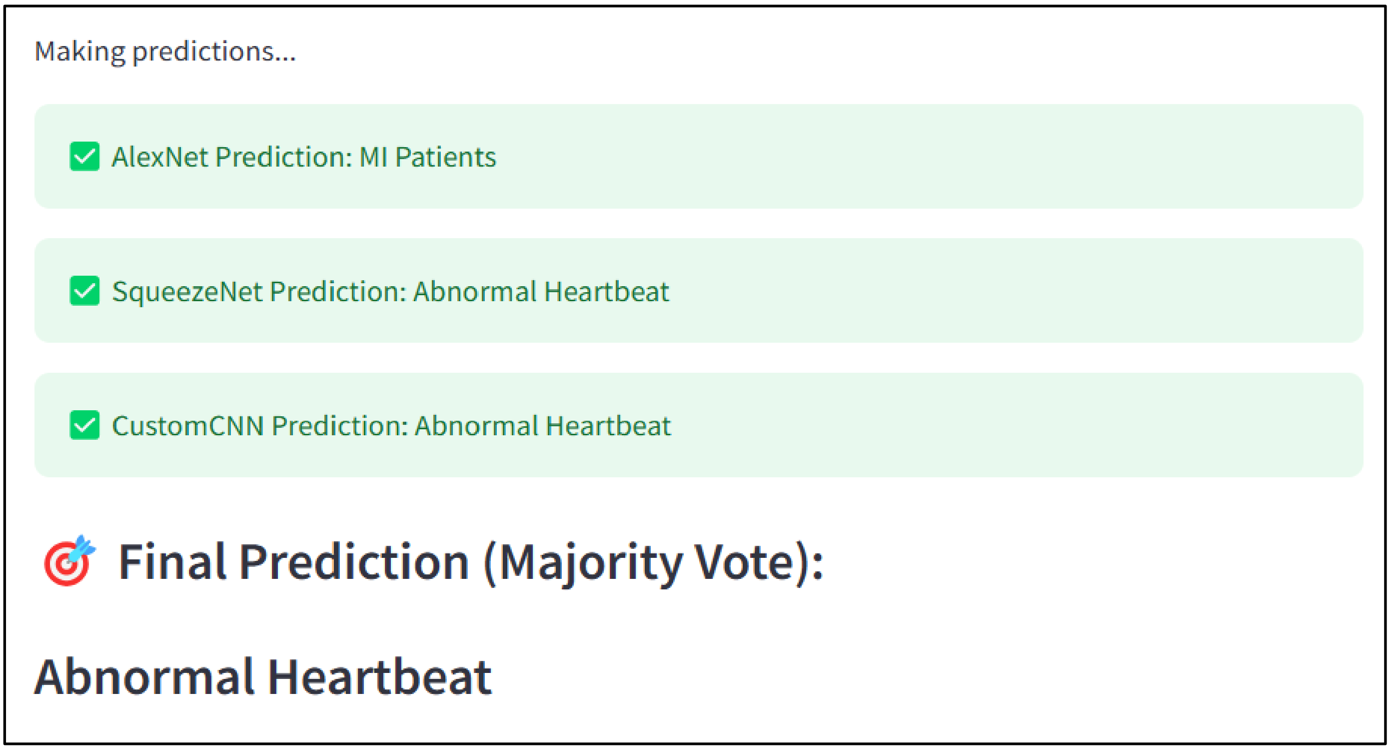

Fig 5 Output of the Prediction System Showing Individual Model Results (Alex net, Squeeze net, and Custom CNN) and the Final Classification Based on Majority Voting for Cardiovascular Disease Detection.

V. RESULTS AND DISCUSSION

This section shows the results obtained from the experiments conducted on the ECG image dataset using three deep learning models: AlexNet, SqueezeNet, and a custom-built CNN architecture.

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Table 1 Performance Measures for Squeeze net, Alexnet and Custom CNN Model

	Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
0	AlexNet	88.362069	88.706099	88.362069	88.498721
1	SqueezeNet	81.250000	82.848526	81.250000	81.005478
2	CNN	100.000000	100.000000	100.000000	100.000000

Each model is evaluated based on performance measures accuracy, precision, recall, F1-score, and confusion matrix, providing insight into their performance in detecting cardiovascular diseases. The pretrained models, AlexNet and SqueezeNet, performed well with moderate computational requirements, showcasing the utility of transfer learning. AlexNet delivered a strong performance with 88% accuracy, benefiting from its deeper architecture and large receptive fields. SqueezeNet, while more lightweight, showed slightly lower accuracy at 81%, which is expected due to its design focusing on parameter efficiency rather than accuracy. The Custom CNN, designed with two parallel branches—stack and full—demonstrated outstanding performance. This architecture allowed the network to learn both localized and global features simultaneously. Techniques such as batch normalization, leaky ReLU activations, and dropout regularization contributed to robust learning and generalization, preventing overfitting despite the high model complexity.

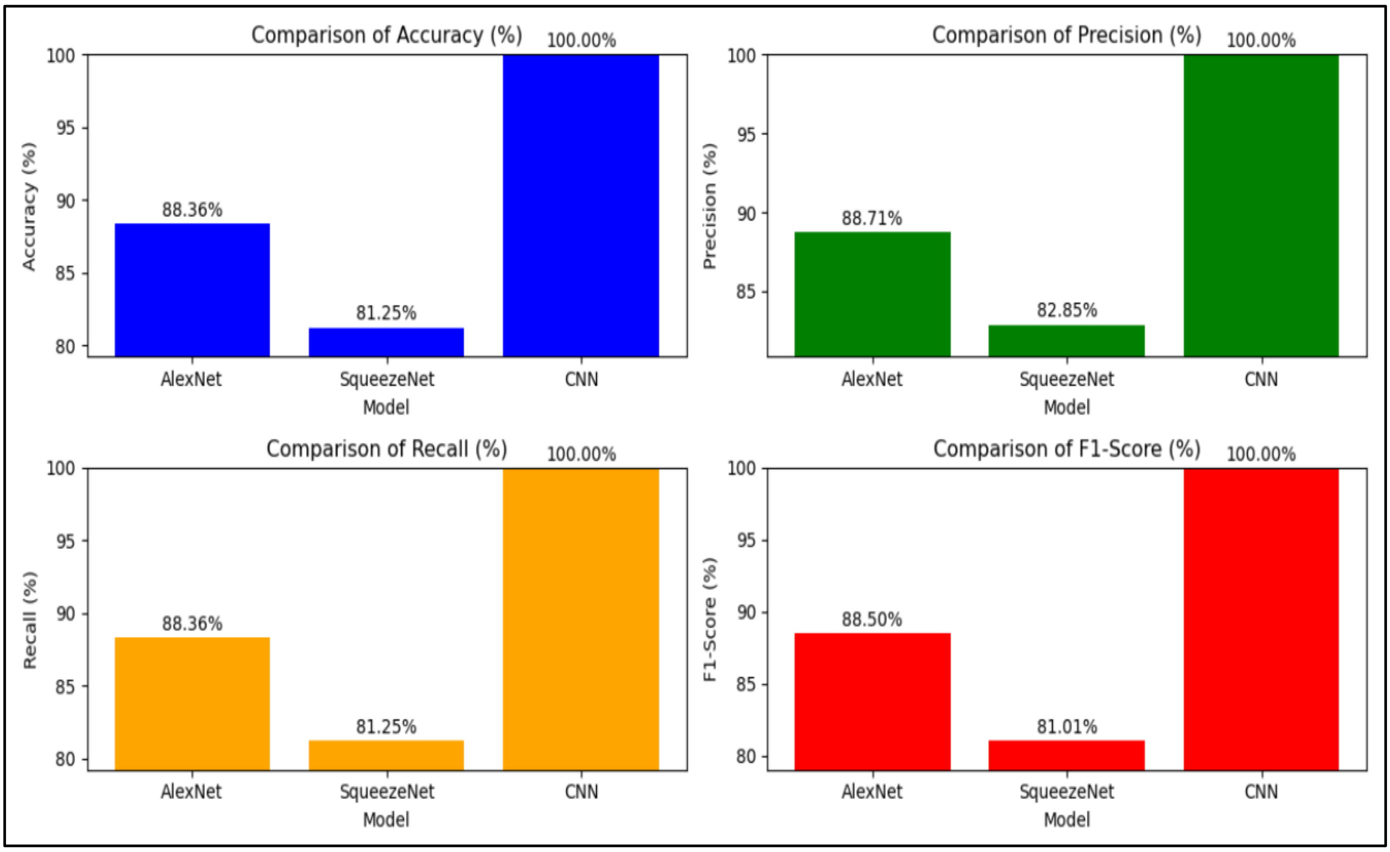

Fig 6 Plots of Performance Measures

To improve the accuracy of predictions, a majority voting approach was adopted, where the final classification decision is determined by the agreement of three distinct models—alexnet, squeezenet, and a custom cnn architecture. By combining multiple models, this approach greatly enhances the accuracy of predictions, as it reduces the impact of individual model biases or occasional errors in classification. By combining predictions from multiple models, the system minimizes the impact of minor differences in individual model outputs, thereby enhancing the overall reliability of the diagnostic result.

By incorporating these trained models into a streamlit-based web application, real-time inference can be performed directly on uploaded ecg images, providing a seamless user experience. The user interface is intentionally created to be user-friendly, requiring little technical expertise, which makes it well-suited for deployment in diverse settings. These include

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healthcare facilities with limited resources, mobile diagnostic units, and outpatient clinics, where rapid and precise initial evaluations can assist in making prompt clinical choices. Additionally, the lightweight design of the application allows it to run smoothly on systems with only a CPU, eliminating the need for expensive hardware and making it accessible to a wider audience. This system serves as a dependable second-opinion tool, aiding medical professionals in the early detection and screening of cardiovascular conditions.

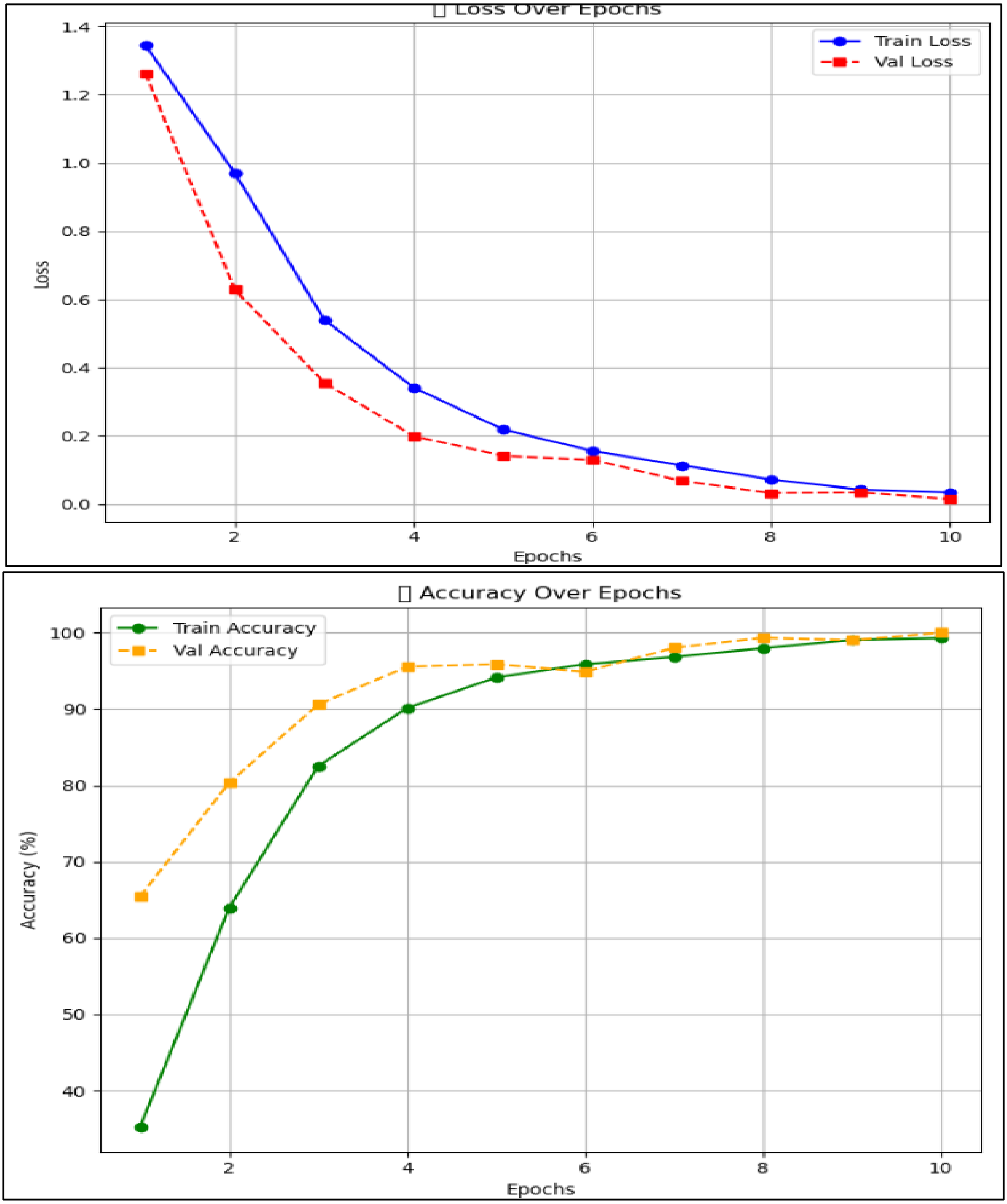

Fig 7 Training and Validation (Loss and Accuracy) View on CNN

VI. CONCLUSION

In this study, we presented an effective approach for the automated detection and classification of cardiovascular diseases using ECG images through deep learning techniques. Three models—AlexNet, SqueezeNet, and a custom-designed CNN—were trained and evaluated on a carefully curated dataset. Among them, the custom CNN architecture outperformed the others, achieving a good classification accuracy of 100%, while AlexNet and SqueezeNet achieved 88% and 81%, respectively.

The experimental results demonstrate the potential of deep learning, particularly CNN-based architectures, in extracting complex patterns from ECG images and providing accurate diagnoses. Moreover, we implemented a Streamlit-based deployment framework to make the system easily accessible for real-time inference, promoting practical applicability in clinical environments.

FUTURE WORK

This study lays a strong foundation for automated cardiovascular disease detection using deep learning on ECG images, but there is ample scope for future enhancements. A key area for improvement involves experimenting with more advanced neural architectures, such as Vision Transformers (ViTs) or attention-based models, which may further improve classification accuracy and model efficiency.

Another promising direction is the use of ensemble learning methods combining predictions from multiple deep learning models to increase robustness and reduce variance. Furthermore, the inclusion of clinical metadata (e.g., age, gender, medical history) alongside ECG images can help develop a more comprehensive and personalized diagnostic model.From a practical standpoint, integrating this system into a real-time web or mobile application using cloud-based deployment platforms could facilitate easy access for healthcare providers. Ongoing work can also focus on enhancing the model's generalizability by testing it across different hospitals, devices, and patient demographics to ensure it performs reliably in diverse clinical environments.

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