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Automated Diagnosis of Cardiac Diseases Using ECG Image Analysis

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Abstract: *This project presents an auto-ECG image analysis-based automated system for the prediction of four key cardiac states of abnormal heartbeat, history of myocardial infarction (MI), myocardial infarction, and normal heartbeat by means of advanced deep learning. The system is quite beneficial in providing accurate results as per ECG data acquired. It also generates follow-ups relevant to the detected condition so that emergency cases can reach for immediate medical intervention and diagnosis. The system is particularly valuable in settings where cardiologists are unavailable, ensuring timely detection and response to critical cardiac issues. A user-friendly web application built using Streamlit allows users to easily upload ECG images, which are then pre-processed and analyzed to deliver fast and reliable diagnoses. This is with the integration of deep learning into accessible technology in the aim to enhance early detection, optimize patient outcomes, and streamline cardiovascular healthcare especially in emergency situations and remote areas.*

Keywords: ECG image Analysis, Cardiovascular Disease Classification, Myocardial Infarction

I. INTRODUCTION

Cardiovascular diseases are a leading cause of death worldwide, claiming millions of lives annually. Early diagnosis and timely medical intervention are crucial to preventing fatalities and minimizing the long-term impacts of these conditions. However, many individuals, particularly those in rural or underserved areas, face significant barriers to accessing specialized care. The lack of cardiologists and advanced diagnostic facilities in these regions often results in delayed diagnoses, leading to poor outcomes such as irreversible cardiac damage or premature death. Bridging this gap in access to timely diagnostics is an urgent need in the global healthcare landscape. This project proposes a novel web-based application developed using Flask, aimed at automating the analysis of ECG (electrocardiogram) images. By integrating cutting-edge deep learning models and advanced image-processing techniques, the system is capable of accurately classifying ECG patterns into four key categories: Myocardial Infarction (MI), History of MI, Abnormal Heartbeat, and Normal Heartbeat. These classifications offer healthcare providers critical diagnostic insights in real-time, enabling prompt decision-making, even in settings where cardiologists are unavailable.

Beyond classification, the application incorporates actionable follow-up recommendations tailored to each diagnostic outcome. For emergency cases, it prioritizes swift medical intervention, ensuring that patients with life-threatening conditions receive immediate care. For non-critical cases, the system provides detailed guidance to support ongoing patient management. This dual approach not only enhances diagnostic accuracy but also ensures the efficient allocation of healthcare resources, reducing the burden on overworked medical professionals.

The driving force behind this project is the vision to democratize access to vital cardiac diagnostics. By leveraging modern technology, the system aims to empower healthcare providers and first responders with an efficient, reliable, and easy-to-use tool. Ultimately, the project aspires to make a significant impact on global health outcomes by facilitating early detection, improving patient management, and reducing mortality rates associated with cardiovascular diseases.

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II. METHODOLOGY

DATA PREPROCESSING ALGORITHM:

1. Read the ECG Image:

Load the ECG image from a source using an image processing library (e.g., OpenCV'simread or PIL's open()). The image serves as the input for the preprocessing pipeline.

2. Divide the Image into Leads:

The ECG image is segmented into 16 smaller regions (leads), representing different views of the heart's electrical signals.

Each lead is carefully extracted using predefined pixel coordinates to ensure that the region of interest is captured accurately.

3. Preprocess Each Lead:

Convert to Grayscale:

▪ The image is converted to grayscale to remove color information, retaining only intensity values that are critical for ECG signal analysis.

▪ This simplifies the data and reduces complexity for machine learning models.

Apply Gaussian Blur:

▪ A Gaussian blur is applied to smooth out high-frequency noise and remove any irrelevant image details.

▪ This helps in focusing on the main ECG signal patterns by reducing unwanted artifacts and enhancing the signal clarity.

Otsu Thresholding:

▪ Otsu's thresholding technique is used to binarize the image, converting it into black and white.

▪ This step highlights the key features of the ECG signal, making it easier to identify peaks and patterns.

4. Resize Each Lead:

All leads are resized to a uniform size of 300x450 pixels.

Resizing ensures that each lead is consistent in terms of dimensions, making it suitable for machine learning models that require fixed-size inputs.

5. Combine Processed Leads:

The individual leads are arranged into a 4x4 grid (16 leads in total) to form a complete view of the ECG signals.

The leads are stacked row-wise to create a single, comprehensive image that captures the overall ECG pattern.

6. Display the Combined Image:

The 4x4 grid image is visualized using libraries like Matplotlib or OpenCV, providing a clear representation of the preprocessed ECG signals.

This visualization allows for easy inspection and interpretation of the ECG data by healthcare professionals or AI models.

7. Outcome:

The preprocessing pipeline outputs a clean, uniform image, making it suitable for machine learning models to analyze.

The final image is ready for classification, where it will be used to predict cardiovascular conditions, such as Myocardial Infarction (MI) or abnormal heartbeats.

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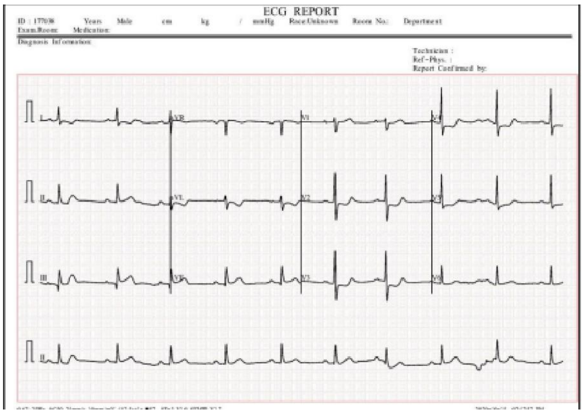
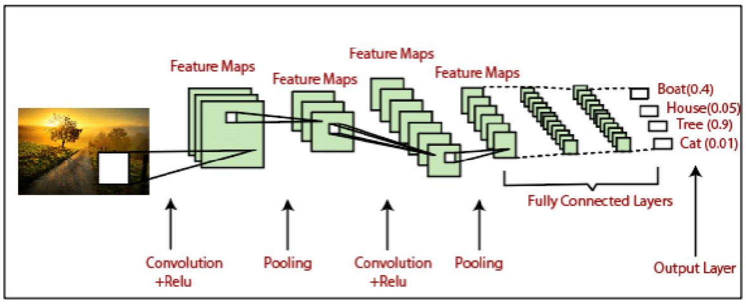


Fig:Image before preprocessing

Fig:Image after preprocessing

Convolutional Neural Networks: Convolutional Neural Networks (CNNs) represent a category of deep learning architectures specifically designed for the analysis and processing of visual information, including images and videos. These networks excel in identifying various patterns, such as edges, textures, shapes, and objects within an image. In the context of each image, patterns are referred to as filters, which serve as feature detectors. CNNs possess the characteristic of location invariance, enabling them to recognize patterns regardless of their position within the image.



How CNN Works:

1. Input Layer • The input is typically an image represented as pixel values in a 2D or 3D matrix (e.g., height × width × channels like RGB).

2. Convolution Layers (Filters) • Filters/Feature Detectors: CNNs use filters (small matrices) to extract specific patterns from the image, such as edges, lines, or textures. • The filter slides over the image (a process called convolution) and calculates a dot product between the filter and parts of the image. This creates a new matrix

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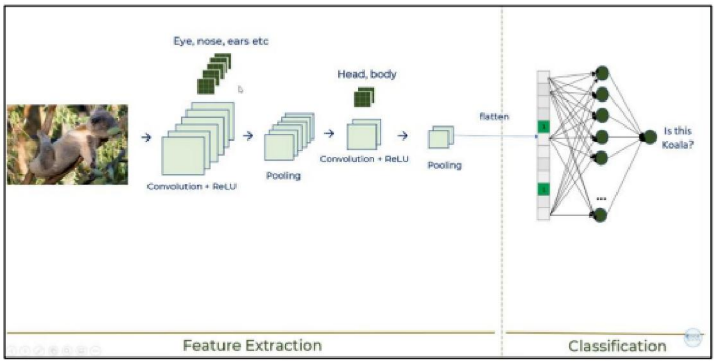
called the feature map. • Key Idea: Filters act as pattern detectors and identify features regardless of their location in the image. This is why CNNs are location invariant.

3. ReLU Activation 22 • After convolution, CNN applies a Rectified Linear Unit (ReLU) to introduce non-linearity, ensuring the model can learn complex patterns.

4. Pooling Layers • These layers downsample the feature maps, reducing their size while preserving essential information. • Example: Max Pooling selects the maximum value in a small window, helping to make the model more location-invariant and efficient.

5. Fully Connected Layers • The high-level feature maps are flattened and passed through fully connected layers to perform tasks like classification or object detection.

6. Output Layer • The final layer uses an activation function like Softmax (for classification) to produce probabilities for each class.



ResNet: ResNet (Residual Network) is a family of convolutional neural networks (CNNs) that were designed to address the challenges of training very deep networks. Introduced by Microsoft Research, ResNet has been highly influential in the field of deep learning. 23

Structure:

Input Layer:

o Takes in images, typically resized to a specific resolution (e.g., 224x224 for ResNet-50).

Initial Convolutional Layer:

o The first convolutional layer uses a 7x7 filter with stride 2 to extract low-level features from the input image. This is followed by batch normalization and ReLU activation.

Max Pooling Layer:

o A max-pooling layer with a 3x3 kernel and stride 2 is applied after the initial convolution to reduce spatial dimensions.

Residual Blocks:

o ResNet is characterized by the use of residual connections (skip connections) that allow the network to skip certain layers, helping to avoid vanishing gradients and improving training performance.

o Each residual block typically includes two or three convolutional layers, along with batch normalization and ReLU activation.

Stage Blocks:

o The network is divided into several stages, each containing multiple residual blocks. The number of filters increases as we move deeper into the network, and the spatial resolution of the feature maps decreases.

o Common architectures like ResNet-50, ResNet-101, and ResNet-152 refer to the number of layers in the network.

Global Average Pooling:

o After the residual blocks, a global average pooling layer is used to reduce the spatial dimensions to a 1x1 spatial map, effectively compressing the feature map into a single value per feature map channel.

Fully Connected Layer:

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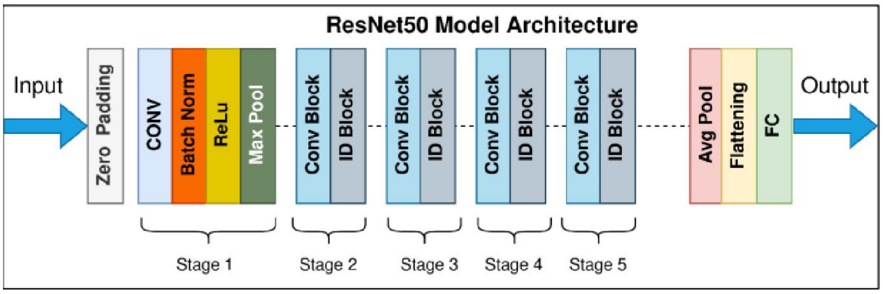
o A fully connected layer with softmax activation is applied for classification, producing the final output class probabilities.



IV. LITERATURE SURVEY

The study Automated ECG Signals Analysis for Cardiac Abnormality Detection by Kaniz Fatema et al. (2024) integrates Discrete Wavelet Transform (DWT) for feature extraction and Principal Component Analysis (PCA) for dimensionality reduction, coupled with Adaptive Neuro-Fuzzy Inference System (ANFIS) for classification. This approach effectively combines neural network learning with fuzzy logic for cardiac abnormality detection. While promising, the system struggles with noise and signal variability, impacting reliability. Additionally, its generalization across diverse populations remains unvalidated, indicating the need for further improvements. This research offers valuable insights but requires refinements for broader clinical application.

The study Enhanced ECG Signal Features Transformation to RGB Matrix Imaging for Advanced Deep Learning Classification of Myocardial Infarction and Cardiac Arrhythmia by Zakaria Khatar and DouniaBentale (2024), published in Springer Multimedia Tools and Applications, introduces a novel technique for ECG analysis. It transforms ECG signals into RGB matrix images by incorporating temporal, frequency, statistical, and spatial features, enabling advanced classification using an adaptive RGB-ResNet architecture. This approach shows promise in accurately detecting myocardial infarction and cardiac arrhythmia. However, the method is computationally intensive and heavily dependent on the quality of preprocessing and data, which poses challenges for its scalability and practical deployment in diverse healthcare environments.

Acharya et al. developed a deep convolutional neural network (CNN) model specifically for heartbeat classification from ECG signals. The model worked in an end-to-end manner, eliminating the need for manual feature extraction. It classified various types of heartbeats with remarkable accuracy, outperforming traditional diagnostic methods. The research demonstrated how CNNs can effectively capture subtle patterns in ECG data. Their work contributed to automating cardiac diagnosis, reducing reliance on expert intervention. The study also discussed the adaptability of the CNN model across different datasets. It paved the way for further advancements in automated cardiac rhythm analysis.

Huy Pham et al. (2023) evaluate multiple machine learning models, including 1D CNN and 1D ResNet, for detecting cardiovascular diseases. The models perform well in classification tasks. However, Poincaré diagram-based models show lower efficiency in multi-class classification tasks. Noise susceptibility remains a major challenge. The study highlights the potential of machine learning in ECG signal analysis. It underscores the need for robust techniques to handle noisy data. Comparative analysis strengthens the research outcomes.

JanbhashaShaik et al. (2023) introduce a method combining a prioritized feature subset with a Generative Adversarial Network (PFSV-AGAN) to generate synthetic ECG signals. A CNN classifier is used for arrhythmia detection and categorization. The approach is innovative in handling complex datasets. However, it faces high computational costs and training complexity. Generalization to diverse datasets is another limitation. The use of GANs is a novel contribution to the field. Further research is required to reduce computational demands.

Nitish Katal et al. (2023) utilize Continuous Wavelet Transform (CWT) to convert ECG signals into scalograms. These scalograms are classified using a custom Convolutional Neural Network (SmallNet). The system achieves high accuracy in arrhythmia detection. However, distinguishing between certain conditions remains difficult. Computational

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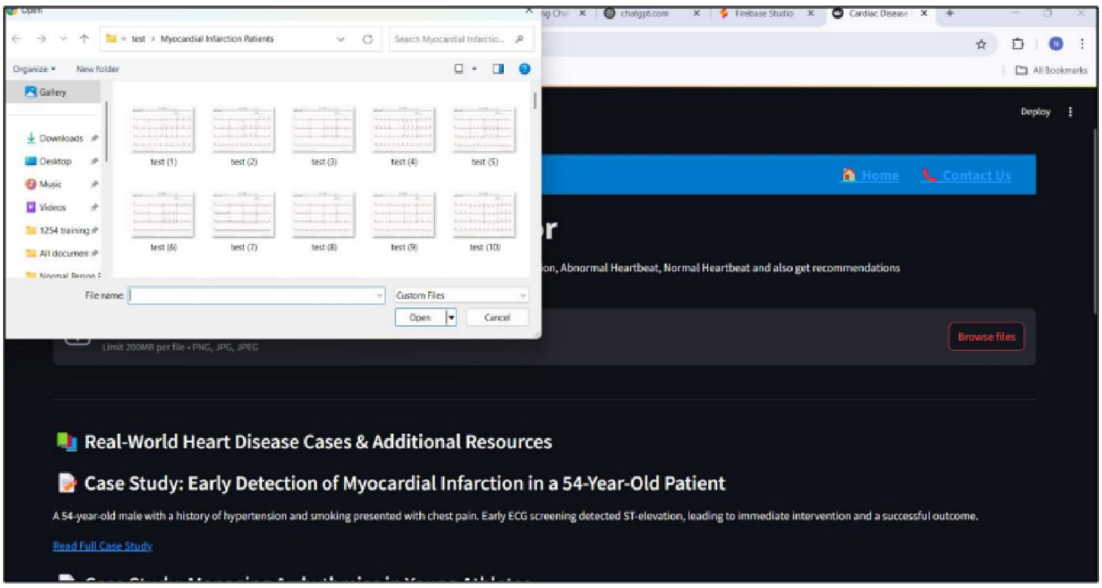
demands could pose challenges in resource-constrained environments. The system demonstrates the power of deep learning in healthcare. Further optimization could make it more practical for widespread use.

Lotfi Mhamdi et al. (2022) use MobileNetV2 and VGG16 models for ECG image classification. The system classifies data into four categories: normal, MI, HMI, and ABH. The method is efficient and achieves high classification accuracy. However, it suffers from model overfitting and lacks diversity in architecture. The approach demonstrates the potential of AI in cardiac disease diagnosis. More robust models and techniques could improve generalization. Reducing overfitting is critical for better performance.

Sodmann et al. proposed a CNN-based framework for annotating ECG signals and classifying cardiac rhythms. Accurate labeling of ECG data was a key focus, as it forms the foundation for reliable classification. Their model handled complex arrhythmias with high robustness and precision. The research highlighted the importance of architecture optimization for processing noisy and diverse ECG signals. The authors demonstrated the potential for integrating their model into real-time healthcare applications. They achieved significant success in automating arrhythmia detection without compromising accuracy. The study underscored the role of AI in improving clinical workflows and patient outcomes..

V. RESULTS

Home page



Input Image Upload

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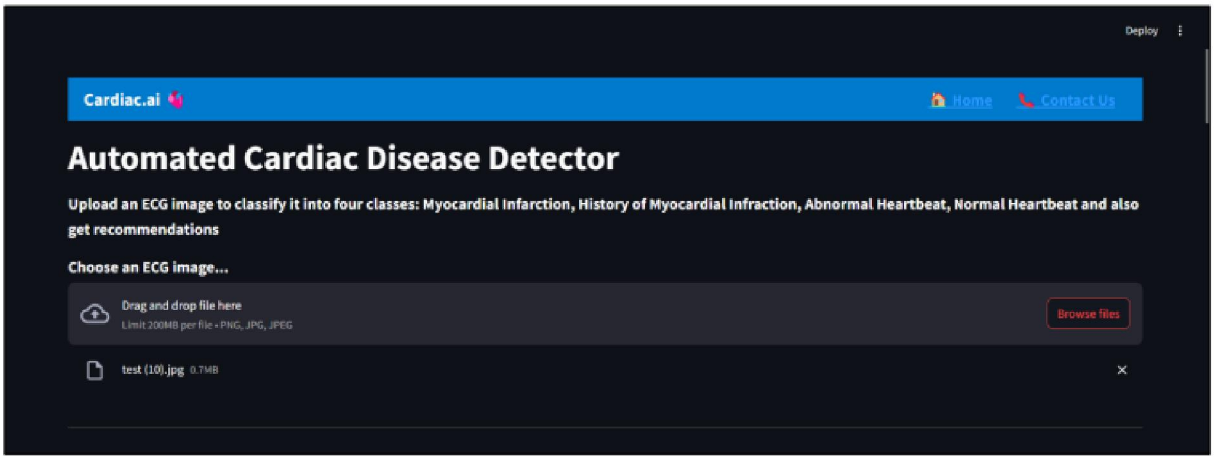
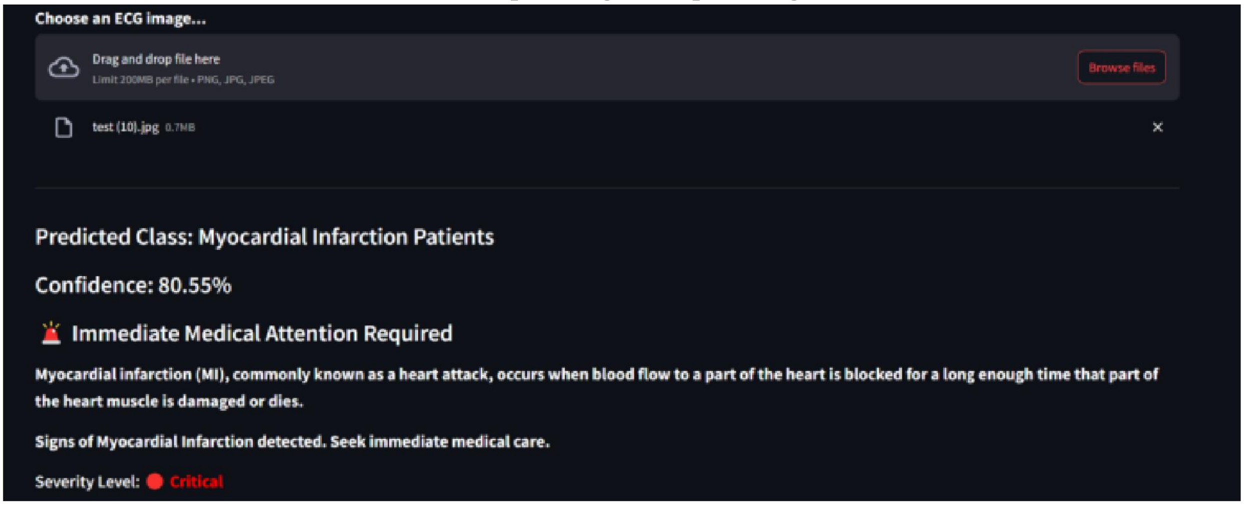
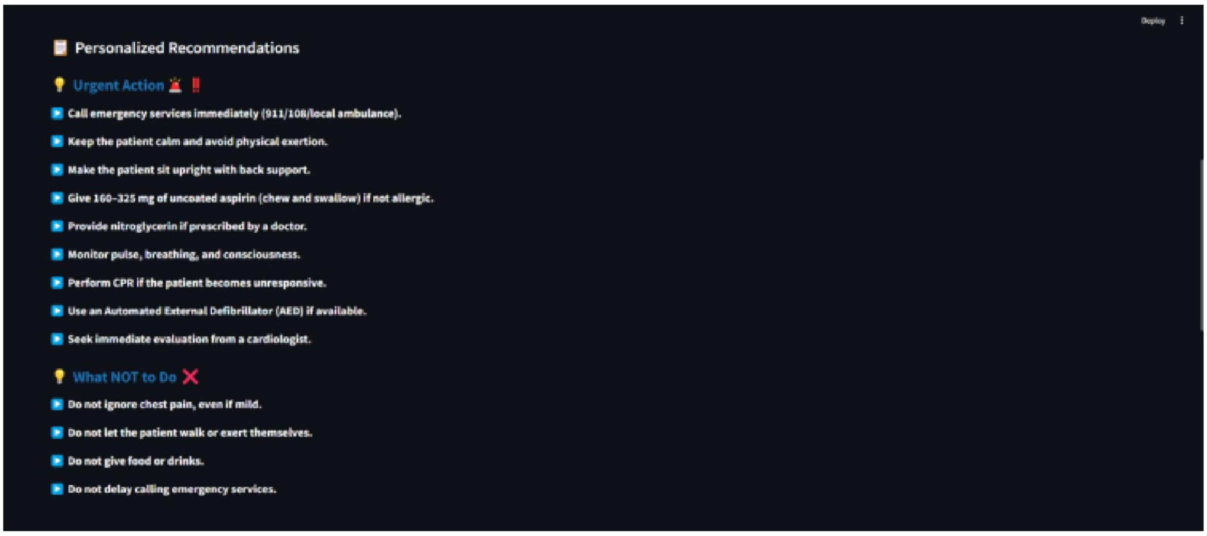


After Uploading the Input Image



Myocardial Infraction



Normal Heartbeat Prediction

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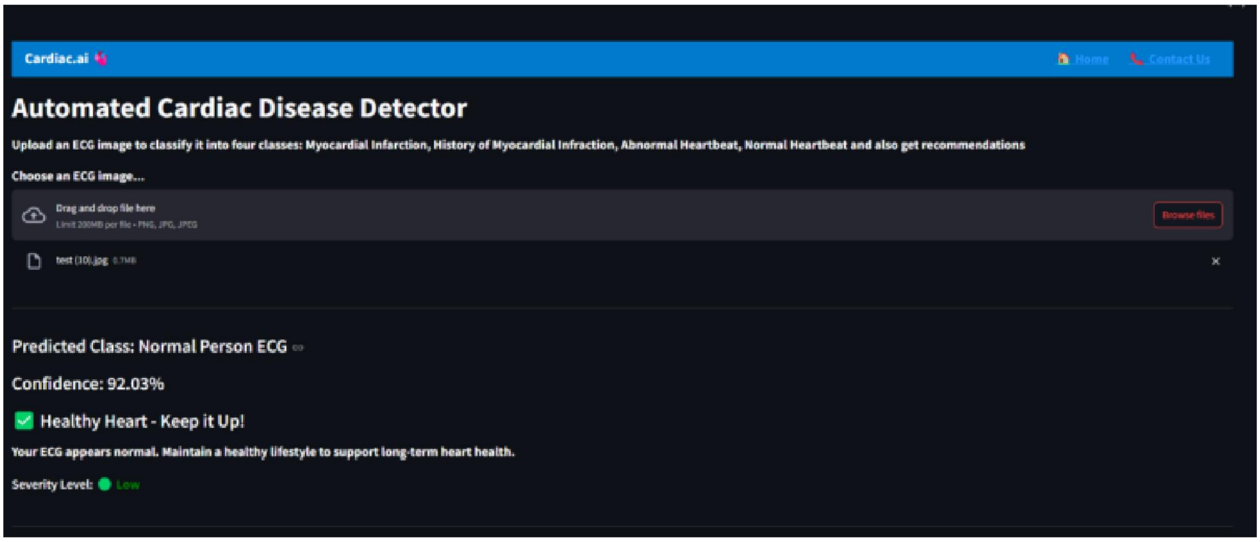
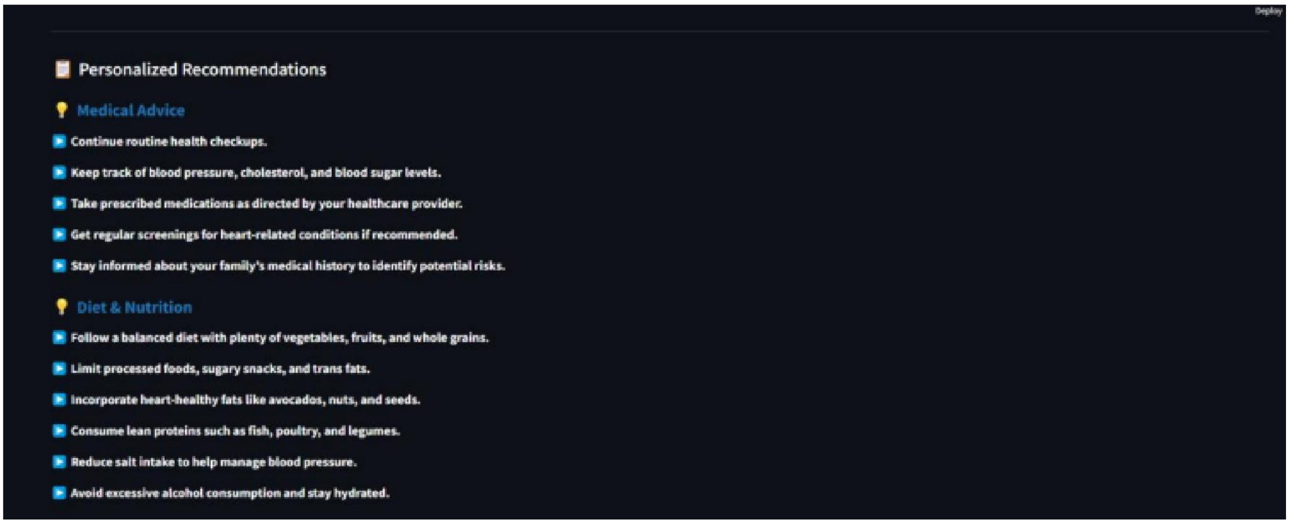
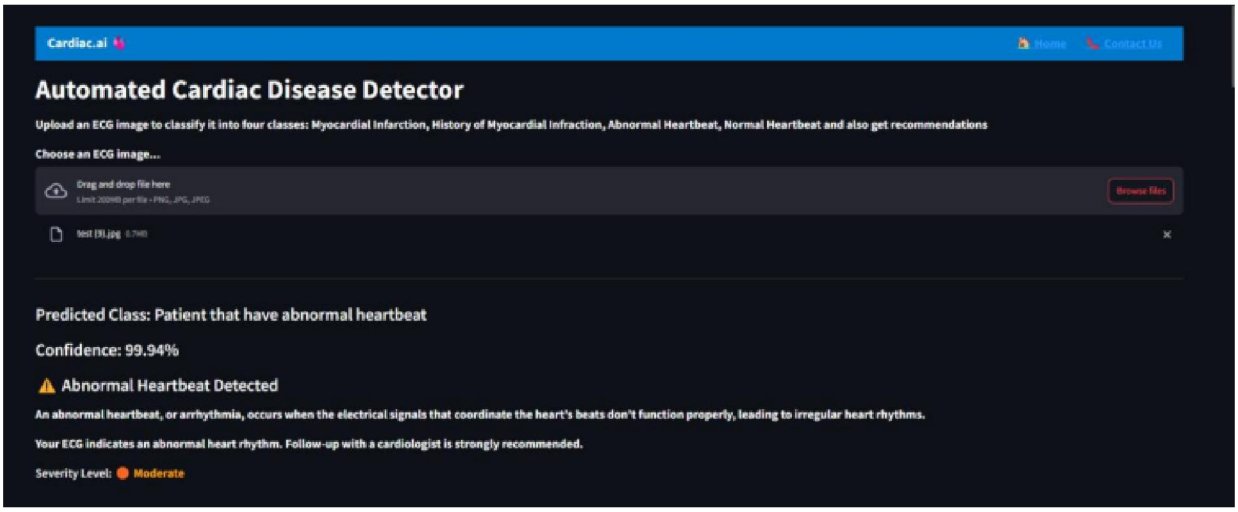


Normal Heartbeat recommendation(1)



Normal Heartbeat recommendation(2)



Abnormal heartbeat prediction

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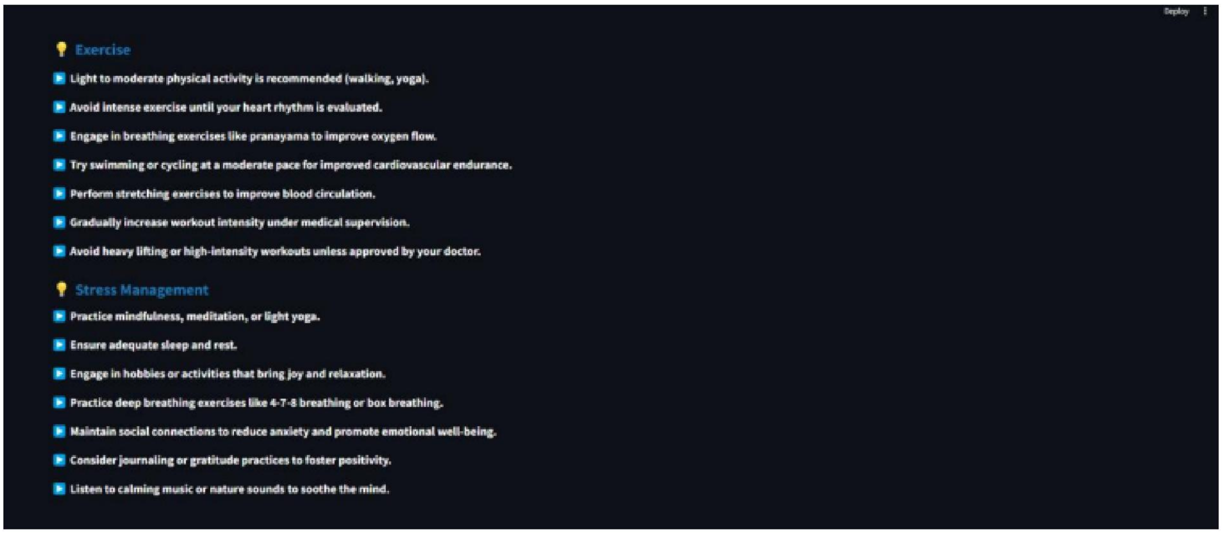
Abnormal heartbeat recommendation(1)

Abnormal heartbeat recommendation(2)



Abnormal heartbeat recommendation(3)

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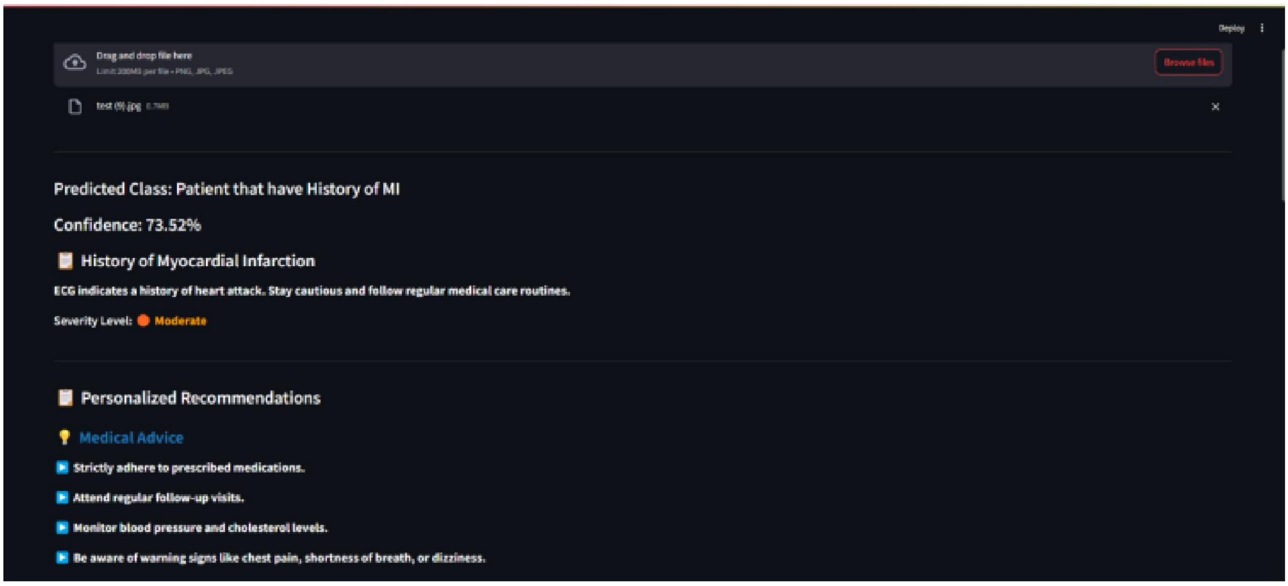

History of ML prediction

History of ML recommendation

VI. CONCLUSION

This project developed an automated system for detecting cardiovascular diseases using ECG image analysis and deep learning. It employs an ensemble of CNN and ResNet models with weighted averaging to accurately classify ECGs into Myocardial Infarction (MI), History of MI, Abnormal Heartbeat, and Normal Heartbeat. The ensemble boosts diagnostic accuracy by leveraging both models' strengths. The system also provides timely lifestyle and medical recommendations, aiding healthcare professionals—especially in under-resourced areas—by reducing diagnostic delays and enhancing patient outcomes. This work contributes to making cardiac disease detection more accessible, efficient, and reliable through AI.

VII. ACKNOWLEDGMENTS

Indeed, the thanks are extended to all those involved in bringing this project on blockchain architecture for pharmaceutical supply chain traceability to completion. This project would not have been made possible without the strong support of dedicated team members, domain experts, and stakeholders intently guiding and collaborating with the project.

To our technical advisors: thank you very much for invaluable input in Ethereum smart contract development and secure system design; it is that which literally defined this tamper-proof, transparent, and decentralized solution. Lastly, we appreciate verbal givings from the pharmaceutical partners and regulatory consultants regarding their experiences from the field.

Thanks to the research and development team for their unending efforts towards formulation of a sturdy architecture that will make changing supply chain visibility, minimizing counterfeiting risks, and beefing public confidence with immutable transaction logs.

It is a collective event meant to raise the bar for integrity, safety, and scalability in the global pharmaceutical supply chains

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