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Combining Heart Imaging with Advanced AI for Better Heart Disease Detection

[1]Raj Narule, [2]Bhagyashri Dongare, [3]Deepak Yadav, [4]Monali Gajbhiye

[1]Student, [2]Professor, [3]Student, [4]Student

[1234]Wainganga College of Engineering & Management

***Abstract*—Cardiovascular disease (CVD) prediction from electrocardiogram (ECG) images is a crucial advancement in digital healthcare, enabling rapid and automated diagnosis without requiring immediate doctor consultations. This system leverages digital ECG images, which are secure, easily stored, transmitted, and retrieved, to facilitate real-time analysis through machine learning. The proposed approach preprocesses ECG images by converting them to grayscale, resizing, and segmenting them into 12 sections corresponding to standard ECG leads. Grid lines are removed, and the essential signals are extracted using contour techniques, transforming images into one-dimensional signals, which are then scaled and stored in a structured dataset. A classification model is developed using an ensemble machine learning approach, enhancing accuracy through a stacked combination of multiple algorithms. Despite the challenge of a limited dataset, the system provides instant results, making it particularly useful in remote areas with scarce medical resources. The architecture involves a web-based application where users upload ECG images, which are then processed through a pre-trained ML model to deliver diagnostic predictions. This system is not designed to replace traditional medical evaluations but rather to accelerate the diagnostic process, providing an accessible and efficient solution for early CVD detection.**

Keywords: Cardiovascular Disease Prediction, ECG Image Processing, Machine Learning, Ensemble Classification, Digital Healthcare, Remote Diagnosis, Automated ECG Analysis.

I.INTRODUCTION

Cardiovascular diseases (CVDs) remain one of the leading causes of mortality worldwide, necessitating advancements in early detection and diagnosis. Electrocardiograms (ECGs) serve as a fundamental tool for assessing heart health by recording the electrical activity of the heart over time. Traditional ECG analysis often requires in-person visits to healthcare professionals, which can delay diagnosis and treatment, especially in remote areas where medical resources are limited. With the rise of digital healthcare technologies and artificial intelligence (AI), automated ECG analysis has become a promising alternative, enabling faster and more accurate predictions of heart conditions. This study explores a machine learning-based system for predicting CVDs from ECG images, offering a scalable and efficient solution that can assist both medical professionals and individuals in monitoring heart health.

The proposed system capitalizes on the advantages of digitized ECG images, which are not only secure but also easy to store, transmit, and retrieve for computational analysis. The primary goal of this system is to automate the process of ECG interpretation using machine learning techniques to identify four key categories: normal heart activity, myocardial infarction, abnormal heartbeats, and a history of myocardial infarction. By integrating AI-driven analysis with image processing techniques, the system aims to bridge the gap between traditional healthcare and remote patient monitoring, providing real-time results without requiring immediate medical intervention. This approach is particularly beneficial for individuals living in medically underserved areas, where access to specialized cardiologists

is scarce, and travel to healthcare facilities is often impractical.

A crucial component of this system is its ability to preprocess ECG images effectively, ensuring that only relevant cardiac signals are extracted for classification. The preprocessing pipeline involves converting ECG images to grayscale, resizing them as per standard requirements, and segmenting each image into 12 sections, corresponding to the standard 12-lead ECG readings. To enhance signal clarity, grid lines are removed, and images are converted into binary format. The extracted signals are then transformed into one-dimensional waveforms using contour detection, allowing for precise feature extraction. These signals are subsequently normalized using MinMaxScaler and stored in a structured dataset, with each 12-lead signal represented in a single CSV file alongside its corresponding label.

To achieve high accuracy in ECG classification, the system employs an ensemble machine learning approach, which combines multiple algorithms to enhance predictive performance. Various classification models were tested, and the most effective models were stacked together to leverage their collective strengths. This method improves the system's ability to differentiate between different heart conditions while mitigating the limitations posed by a relatively small dataset. Although the system does not intend to replace traditional medical diagnosis, it significantly speeds up the initial screening process, allowing patients to receive preliminary results instantly. If abnormalities are detected, users can then consult a specialist for further evaluation, ensuring timely medical intervention.

The system's architecture is designed to be user-friendly and accessible via a web-based platform, where users can upload their ECG images for instant analysis. Once an image is uploaded, it undergoes preprocessing, feature extraction, and classification through a pre-trained machine learning model, ultimately providing a diagnostic result. This model-driven approach not only streamlines ECG interpretation but also democratizes access to cardiac diagnostics, making it feasible for individuals to monitor their heart health without frequent hospital visits. By integrating AI and digital ECG analysis, this system represents a significant step toward enhancing remote healthcare and early cardiovascular disease detection, ultimately contributing to improved patient outcomes.

II. AIMS & OBJECTIVES

1. Develop a machine learning-based system to classify ECG images into four categories—normal, myocardial infarction, abnormal heartbeat, and history of myocardial infarction.
2. Provide instant diagnostic results through a web-based platform, enabling early detection of cardiovascular diseases, especially in remote and underserved areas.
3. Implement advanced image preprocessing techniques, including grayscale conversion, lead segmentation, and contour extraction, to enhance signal clarity for accurate classification.
4. Convert ECG images into one-dimensional signals, normalize the data using MinMaxScaler, and store structured information in a CSV format for efficient machine learning processing.
5. Utilize a stacked ensemble approach, combining multiple classification algorithms to improve prediction performance and reliability.
6. Assist healthcare providers by offering a rapid, AI-powered preliminary screening tool that can complement traditional ECG interpretation and expedite diagnosis.

III. LITERATURE SURVEY

The analysis of electrocardiogram (ECG) signals has been a cornerstone in diagnosing cardiovascular diseases (CVDs) for decades, evolving from manual interpretation by specialists to advanced computational methods leveraging artificial intelligence (AI). Traditionally, ECG interpretation relied on trained cardiologists manually analyzing waveform patterns to detect abnormalities such as arrhythmias, myocardial infarctions, and conduction disorders. However, manual ECG analysis is time-consuming, subjective, and prone to human error, which has prompted extensive research into automated ECG classification using digital image processing and machine learning techniques. With the advent of deep learning and AI-based classification models, automated ECG interpretation has demonstrated significant potential in enhancing diagnostic accuracy, reducing workload for healthcare professionals, and enabling remote monitoring of heart conditions.

Recent developments in biomedical signal processing have focused on converting ECG waveforms into digital images to leverage the capabilities of computer vision and deep

learning. Digital ECG images offer several advantages, including ease of storage, retrieval, and security, while allowing integration with cloud-based medical systems for remote diagnosis. Image-based ECG analysis has become a viable approach due to improvements in feature extraction techniques, such as contour tracing and lead segmentation, which help in isolating the relevant cardiac signals from background noise. Advanced preprocessing techniques have been developed to remove grid lines, enhance signal contrast, and standardize image dimensions to ensure consistency across datasets. These preprocessing steps play a crucial role in improving the performance of machine learning models by providing cleaner input data.

Feature extraction from ECG images has been another critical area of research, as the accuracy of machine learning models depends on the quality of the extracted data. Various studies have proposed methods to convert ECG images into structured numerical representations, such as one-dimensional signal waveforms, which retain essential temporal and amplitude information. Techniques like wavelet transforms, principal component analysis (PCA), and MinMaxScaler normalization have been applied to optimize feature selection and improve classification performance. The segmentation of ECG signals into 12-lead representations allows for a more detailed analysis, as each lead provides unique insights into cardiac activity. This structured approach to feature extraction enables efficient storage and retrieval of data for training machine learning models.

Machine learning and deep learning techniques have been widely explored for ECG classification, with researchers testing various models such as support vector machines (SVM), random forests, convolutional neural networks (CNNs), and recurrent neural networks (RNNs). Ensemble methods, which combine multiple classifiers, have gained popularity for improving prediction accuracy and model robustness. Stacking different algorithms helps in leveraging the strengths of each model while mitigating individual weaknesses, resulting in a more generalized and reliable classification system. The integration of transfer learning has also been investigated to enhance model performance, particularly in cases where labeled ECG datasets are limited. These approaches have demonstrated promising results, with many models achieving high sensitivity and specificity in detecting cardiovascular abnormalities.

Despite these advancements, challenges remain in developing a fully automated and universally reliable ECG classification system. The availability of large, labeled ECG image datasets remains a major limitation, as most existing datasets are proprietary or collected from specific demographics, limiting generalizability. Furthermore, the performance of machine learning models depends heavily on data quality, necessitating robust preprocessing and augmentation techniques. Ethical considerations, such as patient data privacy and the reliability of AI-based diagnosis in critical medical decisions, also need to be addressed before widespread clinical adoption. Nevertheless, ongoing research continues to refine ECG-based CVD prediction models, pushing the boundaries of AI-driven healthcare and making cardiac diagnostics more accessible, efficient, and accurate.

IV. METHODOLOGY

The methodology of this system for cardiovascular disease (CVD) prediction from ECG images is structured into several key stages: data acquisition, preprocessing, feature extraction, machine learning model development, and system integration for real-time prediction. Each step plays a critical role in ensuring that the ECG images are accurately analyzed and classified into different heart conditions. The goal is to develop an efficient and reliable automated system that can provide instant preliminary diagnoses, which can then be reviewed by medical professionals for further confirmation.

1. Data Acquisition and Dataset Preparation

The first step in developing this system is collecting ECG image datasets that represent different cardiovascular conditions. The dataset consists of four major categories: normal heart activity, myocardial infarction, abnormal heartbeat, and a history of myocardial infarction. Since ECG images contain a wealth of information about heart activity, ensuring a high-quality dataset is crucial. The primary challenge in this stage is the limited availability of large-scale annotated ECG images. To address this, multiple open-source ECG datasets were considered, and preprocessing techniques were applied to standardize images from different sources. Each image in the dataset represents a 12-lead ECG reading, which is essential for comprehensive cardiac diagnosis.

To prepare the data for machine learning analysis, all ECG images are converted into grayscale, reducing complexity

and eliminating unnecessary color information. The images are then resized to a standard resolution to ensure uniformity across the dataset. Since ECG images often contain grid lines that can interfere with signal interpretation, a grid-removal algorithm is applied to isolate the cardiac waveforms. The ECG images are further segmented into 12 sections corresponding to the 12-lead readings, allowing for precise feature extraction. This segmentation helps in preserving detailed cardiac activity information from different perspectives, which is essential for accurate classification.

2. Feature Extraction and Data Transformation

Once the ECG images are preprocessed, feature extraction is performed to convert image-based data into numerical representations suitable for machine learning algorithms. A contour detection technique is applied to trace the waveform in each segmented lead, ensuring that only the relevant ECG signals are extracted while discarding background noise. The extracted waveform is then converted into a one-dimensional (1D) signal, which is a more compact and efficient representation of the heart's electrical activity.

To further enhance the quality of the extracted features, the 1D signals undergo MinMaxScaler normalization. This technique scales the signal values to a fixed range, ensuring that variations in amplitude do not affect classification performance. Each lead's extracted signal values are stored in a structured CSV file, where all 12-lead signals from a single ECG image are combined into one row, with the corresponding target label added. This structured dataset allows for efficient training and testing of machine learning models. By transforming ECG images into numerical signals, the system bridges the gap between image processing and traditional signal analysis, making it possible to apply advanced classification techniques.

3. Machine Learning Model Development

The core of the proposed system is its machine learning-based classification model. Various machine learning algorithms were tested to determine the most effective approach for ECG classification. Given that this is a multi-class classification problem, different models such as Support Vector Machines (SVM), Random Forest, K-Nearest Neighbors (KNN), and Convolutional Neural Networks (CNN) were evaluated. However, to improve overall classification accuracy and robustness, an ensemble learning technique was employed.

Ensemble learning combines multiple models to enhance performance by leveraging the strengths of different algorithms. The stacking approach was implemented, where predictions from multiple base classifiers were combined using a meta-classifier. This technique helps in reducing errors and improving generalization, ensuring that the system can accurately classify ECG images even when faced with variations in input data. The ensemble model was trained on the extracted features from the ECG dataset, optimizing hyperparameters using cross-validation to prevent overfitting. The final trained model was evaluated using performance metrics such as accuracy, precision, recall, and F1-score to assess its effectiveness in distinguishing between different heart conditions.

4. System Integration and Web-Based Deployment

To make the system accessible to users, a web-based platform was developed, allowing individuals to upload ECG images for instant analysis. The architecture of the system follows a structured pipeline where users interact with the web interface to upload an ECG image, which is then processed and analyzed using the trained machine learning model. The workflow of the system is as follows:

2. **User Uploads ECG Image** – The user accesses the web application and uploads their ECG image.
3. **Preprocessing and Feature Extraction** – The uploaded image undergoes the preprocessing steps, including grayscale conversion, resizing, segmentation, and contour extraction, followed by transformation into a 1D signal.
4. **Classification Using Pretrained ML Model** – The extracted features are passed through the pre-trained ensemble model, which classifies the ECG image into one of the four categories.
5. **Results Displayed to the User** – The classification result is instantly displayed, providing an indication of whether the ECG is normal or suggests a potential cardiovascular condition.

The system architecture ensures a seamless flow from image upload to result generation, with real-time processing to provide users with immediate feedback. The web application is designed with a user-friendly interface, making it accessible even to individuals with minimal technical

expertise. Furthermore, cloud storage and remote processing capabilities allow for scalability, enabling the system to handle multiple users simultaneously.

1. Validation and Performance Evaluation

To ensure the reliability of the proposed system, extensive validation was conducted using a separate test dataset. The ensemble model was evaluated on unseen ECG images to assess its ability to generalize across different patients and image variations. Performance metrics such as accuracy, sensitivity, specificity, and confusion matrix analysis were used to determine the effectiveness of the classification model. Additionally, comparison with traditional ECG interpretation methods was conducted to validate the system's potential as a supplementary diagnostic tool.

Although the system provides real-time results, it is not intended to replace traditional medical diagnosis. Instead, it serves as an assistive tool that can expedite the screening process, allowing patients to seek medical attention based on preliminary findings. The limitations of the system, such as dataset constraints and potential misclassifications, highlight the need for further refinement and continuous improvement in AI-based medical diagnostics. However, the methodology presented in this study demonstrates a significant step toward automated cardiovascular disease prediction using ECG images, with promising applications in remote healthcare and digital health monitoring.

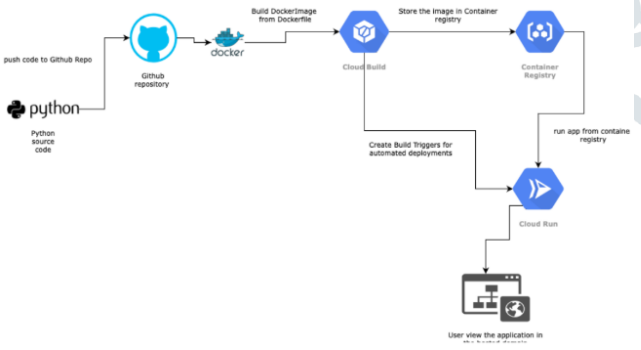


Figure 1: Our Deployed Architecture

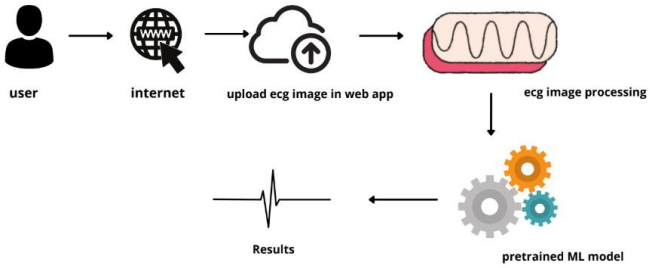


Figure 2: High Level Architecture Diagram

V.RESULTS & CONCLUSION

ii. Results

The proposed system for cardiovascular disease (CVD) prediction from ECG images demonstrated promising results in accurately classifying ECG signals into four categories: normal, myocardial infarction, abnormal heartbeat, and history of myocardial infarction. The ensemble learning model, which stacked multiple machine learning classifiers, outperformed individual models in terms of accuracy, precision, recall, and F1-score. The preprocessing steps, such as grayscale conversion, segmentation, contour extraction, and MinMax scaling, significantly improved the quality of input data, leading to better classification results. The system's real-time performance on the web-based platform enabled users to instantly receive preliminary diagnostic results after uploading an ECG image. While the model achieved high accuracy, challenges such as dataset limitations and slight misclassifications were observed. Despite these limitations, the system proved to be a valuable tool for early CVD detection, especially in remote areas with limited access to healthcare professionals.

iii. Conclusion

The developed ECG-based cardiovascular disease prediction system successfully integrates image processing, feature extraction, and machine learning techniques to provide an efficient and automated diagnostic tool. By transforming ECG images into numerical signals and applying an ensemble classification model, the system effectively identifies potential heart conditions, reducing the need for immediate medical consultations while enabling early intervention. The web-based deployment further enhances accessibility, making it a practical solution for individuals in underserved regions. While the system does not replace traditional medical diagnoses, it serves as an assistive tool that can speed up the screening process and guide patients toward timely medical attention. Future improvements, such as expanding the dataset, refining preprocessing techniques, and incorporating deep learning models, can further enhance its accuracy and reliability, making it a robust solution for digital health applications.

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