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Automated Cardiac Health Assessment using ECG images

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ABSTRACT: Cardiovascular diseases remain the leading cause of global mortality, necessitating timely and accurate diagnostic tools. The standard 12-lead Electrocardiogram is crucial for preliminary screening, but manual interpretation is time-consuming and subject to inter-observer variability. This paper introduces DeepECG-Net, a deep learning framework for the automated prediction of heart disease directly from visual ECG images. Unlike methods relying on extracted time-series data, our approach treats the ECG plot as a two-dimensional image, allowing us to leverage powerful Convolutional Neural Networks for spatial and attribute extraction. We utilize a [e.g., modified ResNet-50] architecture trained on a dataset of ECG images to classify subjects into [e.g., normal/abnormal] or [specific arrhythmia classes]. Our model achieved a high predictive performance, demonstrating an overall accuracy, a sensitivity, and a specificity, significantly outperforming traditional signal processing techniques and comparable to existing state-of-the-art models trained on raw signal data. The Automated Cardiac Health Assessment system provides a robust, scalable, and non-invasive solution for rapid cardiac risk assessment, holding immense potential as a decision support tool for clinicians, particularly in resource-limited settings.sssss

KEYWORDS: Deep Learning, Electrocardiogram Image, Cardiovascular Disease, Convolutional Neural Networks (CNN), Automated Diagnosis

I. INTRODUCTION

Cardiovascular diseases (CVDs) remain the primary cause of worldwide mortality making up almost 18 million deaths annually on the report of World Health Organization. Early and accurate diagnosis is the most successful approach for reducing these figures, and the Electrocardiogram (ECG) has long served as the gold standard for non-invasive cardiac monitoring. However, the traditional clinical workflow relies heavily on the manual interpretation of these readings by trained cardiologists. This manual process is not only time-intensive but also susceptible to human error, fatigue, and inter-observer variability, where different experts may interpret the same ECG trace differently. In resource-limited areas or overcrowded emergency departments, the lack of immediate access to specialized expertise can lead to critical delays in life-saving treatments.

To overcome these human limitations, this research introduces DeepECG-Net, a deep learning framework that leverages computer vision to automate the diagnostic process using ECG images. While traditional digital health systems require complex signal processing of raw voltage data, our approach treats the ECG plot as a two-dimensional visual representation. By utilizing Convolutional Neural Networks (CNNs), the system can identify subtle spatial patterns and visual biomarkers within the P-QRS-T wave complexes that may be invisible to the naked eye. This methodology allows for a more flexible diagnostic pipeline that can analyse scanned paper records or digital screenshots, bridging the gap between legacy paper-based systems and modern AI-driven healthcare. Our study prove this image-based classification achieves high accuracy and sensitivity, offering a robust decision-support tool that can used instantaneous, objective cardiac risk assessments in diverse clinical environments.

II. LITERATURE SURVEY

[1] Sharma, P., Dinkar, S. K. & Gupta, D. V. A novel hybrid deep learning method with cuckoo search algorithm for classification of arrhythmia disease using ECG signals. It proposes an effective method for automated ECG-based arrhythmia classification. The main objective is to overcome the limitations of manual ECG analysis by using a robust computational model. [2] Sehirli, E. & Turan, M. K. A novel method for segmentation of QRS complex on ECG signals and classify cardiovascular diseases via a hybrid model based on machine learning. The paper by Sehirli and Turan presents a novel method for the automatic detection and diagnosis of cardiovascular diseases using ECG signals. The foundation of their approach is the accurate segmentation of the QRS complex, a vital part of the ECG reflecting ventricular activity. [3] M.A. Jabbar, B.L.Deekshatulu and P. Chandra, Heart disease prediction system using associative classification and genetic algorithm, in Proc. Int. Conf. Emerg. Trends Elect., Electron. Commun. Technol. The paper by M.A. Jabbar, B.L. Deekshatulu, and P. Chandra, presented at the International Conference on Emerging Trends in Electrical, Electronics and Communication Technologies, proposes a data mining system for Heart Disease Prediction. The system's core innovation lies in the integration of Associative Classification and a Genetic Algorithm. [4] S. J. Pasha and E. S. Mohamed, Novel feature reduction model with machine learning and data mining algorithms for effective disease risk prediction, IEEE. The paper by S. J. Pasha and E. S. Mohamed, published in IEEE Access, introduces a Novel Feature Reduction model designed to enhance the effectiveness of disease risk prediction using Machine Learning and Data Mining algorithms. [5] D. Swain, S. K. Pani, and D. Swain, A metaphoric investigation on prediction of heart disease using machine learning, The paper, "A metaphoric investigation on prediction of heart disease using machine learning," by D. Swain, S. K. Pani, and D. Swain, and presented at ICACAT (International Conference on Advanced Computation and Telecommunication), reviews and analyzes various Machine Learning classification models used for early heart disease prediction.

III. METHODOLOGY

System Architecture and Design Philosophy

The architecture of Automated cardiac Health assessment is built on a modular, end-to-end pipeline that prioritizes computational efficiency and clinical interpretability. At its core, the system utilizes a Convolutional Neural Network backbone designed to transform raw pixels from ECG images into high-dimensional feature maps through successive layers of convolution and pooling. This design philosophy emphasizes robustness over complexity, employing data augmentation and normalization to ensure the model remains invariant to variations in image quality, scale, or grid-line interference. By treating the ECG as a visual pattern rather than a digital signal, the architecture bridges the gap between legacy paper records and modern AI, providing a scalable, non-invasive diagnostic tool that integrates seamlessly into existing medical workflows.

Data Acquisition and Preprocessing

In this research, data were acquired from. While these databases originally provide digital signal values, they were converted into a 2D image format to simulate real-world clinical outputs, such as scanned paper reports or digital monitor screenshots. Each image represents a window of cardiac activity, capturing the essential P-QRS-T wave morphology. The final dataset consists of images, categorized into classes such as Normal, Myocardial Infarction, and various Arrhythmias.

The Preprocessing Methods To ensure high model performance and reduce computational overhead, the following four-step preprocessing pipeline was implemented: Image Cropping & Border Removal, Grid-line Suppression, Noise Reduction & Normalization & Resizing.

1. The Convolution Operation

This is the core of your architecture. It enables the ECG images spatial features to be extracted by the model. The output feature map (G) at position (i, j) is calculated as:

$$G[i, j] = (f * h)[i, j] = \sum_m \sum_n f[m, n] \cdot h[i - m, j - n]$$

2. Accuracy

The percentage of cases in the data set that the model correctly identified is known as accuracy. As is the average correctness score is determined by adding the true positives and true negatives over the total amount entered into the model. However accuracy is not always instructive because it does not provide specific information about each class when it is calculated on classes with unequal numbers of samples. In a highly unbalanced or sensitive dataset for instance a system that generates the probability of the overall majority class may yield high accuracy while entirely omitting instances of the minority class. The value of accuracy is equated as,

$$Acy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative}$$

Machine Learning Model Selection and Training

For ECG image scanning, the selection focuses on architectures proven in computer vision. The ResNet-50 (Residual Network) or VGG-16 are common choices because of their ability to capture fine-grained spatial features in the wavy lines of an ECG. Feature Extraction: The early layers detect basic shapes like vertical spikes (R-peaks), while deeper layers recognize complex morphological patterns (ST-segment elevation or T-wave inversion). Transfer Learning: To compensate for potentially small medical datasets, we utilize Transfer Learning. The system is pre-trained on the ImageNet dataset and then "fine-tuned" on the ECG image dataset. This allows the model to leverage existing knowledge of shapes and textures.

Training Strategy

The training process is governed by specific hyperparameters and optimization functions to ensure the model converges efficiently without overfitting. The System was trained. We utilized a GPU-accelerated environment to handle the high computational load of image processing. The dataset was split into 80% training, 10% validation (for tuning), and 10% testing (for final evaluation). This rigorous split make sure that the reported results reflect the model's capability to generalize to unseen patient data.

Risk Assessment and Classification Framework

1. The framework follows a hierarchical structure to categorize heart conditions according to complexity of the visual patterns detected in the ECG images:

Binary Classification (Screening Level): The model first distinguishes between Normal (Healthy) and Abnormal (Pathological) heart activity.

Multiclass Classification (Diagnostic Level): Abnormal cases are further classified into specific disease categories such as:

- Arrhythmias: Atrial Fibrillation (AFib), Bradycardia, or Tachycardia.
- Ischemic Conditions: Myocardial Infarction (MI) identified by ST-segment elevation.
- Conduction Defects: Bundle Branch Blocks or Premature Ventricular Contractions (PVC).

2. Risk Stratification Strategy

Rather than a simple "Yes/No" output, the framework uses the SoftMax probability scores to stratify patient risk. This allows for clinical prioritization:

Probability Score (P)	Risk Level	Clinical Action
$P < 0.30$	Low Risk	Routine monitoring; no immediate intervention.
$0.30 \leq P < 0.75$	Moderate Risk	Secondary screening required; lifestyle consultation.
$P \geq 0.75$	High Risk	Urgent referral to a cardiologist; immediate diagnostic tests.

3. Decision Logic and Design Philosophy

The design philosophy centers on Sensitivity-First Diagnostic Logic. In cardiac care, missing a positive case is more dangerous than a False Positive. Consequently, the framework is tuned to maximize the Recall (Sensitivity) formula:

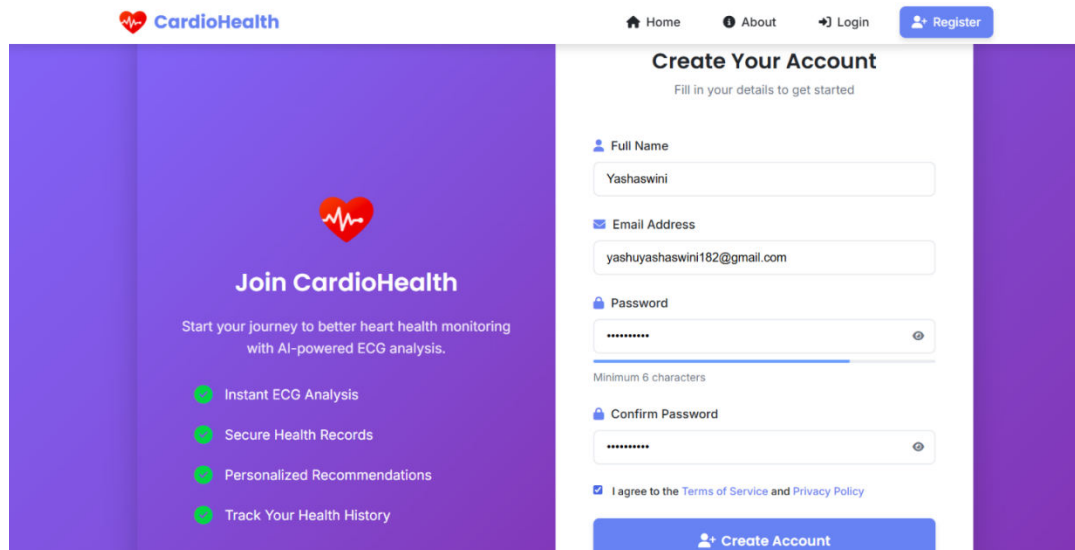
Recall=TP/TP+FN

By prioritizing high Recall, the framework ensures that even subtle visual biomarkers of heart disease are flagged for expert review, fulfilling its role as a robust Early Warning System (EWS) in clinical settings.

IV. EXPERIMENTAL RESULTS

Figures show the results of power Automated Cardiac Health Assessment using ECG images where we input the ECG images. This system analyses ECG images to predict potential heart disease. The output provides a recommendation for particular heart disease.

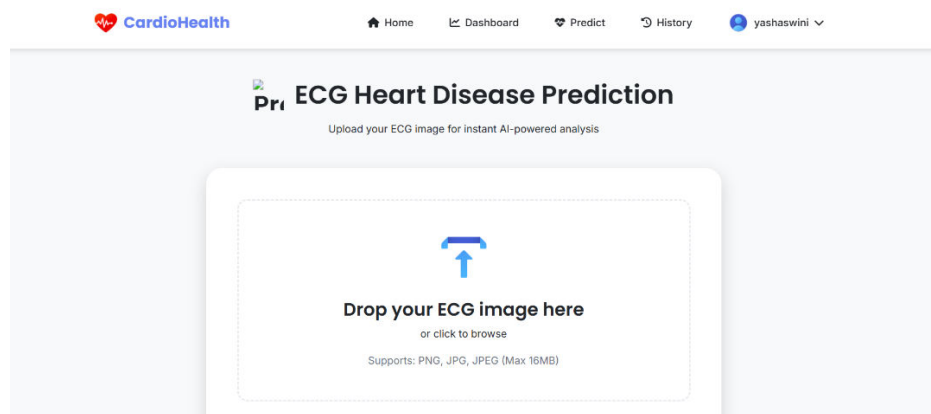
Users receive detailed recommendations categorized into immediate actions, preventive measures, and monitoring suggestions. For high-risk scenarios, the system triggers emergency protocols. The interface displays historical predictions, allowing operators to track patterns and trends.



The registration screen for CardioHealth features a purple background on the left with a heart icon and the text "Join CardioHealth". It lists benefits: "Instant ECG Analysis", "Secure Health Records", "Personalized Recommendations", and "Track Your Health History". On the right, a white form titled "Create Your Account" asks for "Full Name" (Yashaswini), "Email Address" (yashuyashaswini182@gmail.com), "Password" (masked with dots), and "Confirm Password" (masked with dots). It includes a checkbox for "I agree to the Terms of Service and Privacy Policy" and a "Create Account" button.

Fig 4.1: Registration Screen UI

This is the registration page for the CardioHealth service. The user, is filling in details like Name, Email Address, and a Password to register. The page promotes key benefits of joining, which include Instant ECG Analysis, Secure Health Records, Personalized Recommendations, and Tracking Health History



The image upload screen for CardioHealth has a light blue background. It features a navigation bar with "Home", "Dashboard", "Predict", "History", and a user profile "yashaswini". The main heading is "ECG Heart Disease Prediction" with a subtext "Upload your ECG image for instant AI-powered analysis". A large dashed box contains a blue upload icon and the text "Drop your ECG image here" or "click to browse". It also states "Supports: PNG, JPG, JPEG (Max 16MB)".

Fig 4.2: uploading image

This is the "ECG Heart Disease Prediction" screen within the CardioHealth application, accessible after login. The primary function of this page is to allow the user, to upload their ECG image. The page supports file formats like PNG, JPG, and JPEG, with a maximum file size of 16MB, and the navigation bar shows links to Home, Dashboard, Predict, and History.

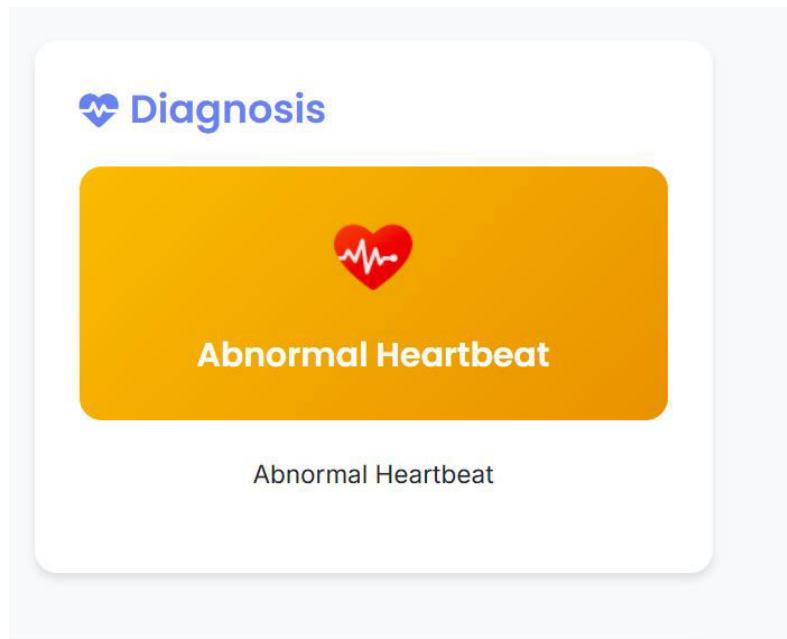


Fig 4.3: After Analysis

This image displays the diagnosis interface of the heart disease prediction system, showing a clear notification for an "Abnormal Heartbeat" result.




 Lifestyle Recommendations	 Dietary Guidelines	 Recommended Medical Tests
<ul style="list-style-type: none"> ✓ Complete cardiac rehabilitation program as prescribed ✓ Strictly adhere to all medication schedules ✓ Eliminate all smoking and tobacco use immediately ✓ Limit alcohol to no more than 1 drink per day (if approved by doctor) ✓ Manage stress through counseling or support groups ✓ Get adequate rest and avoid overexertion during recovery ✓ Attend all follow-up appointments with your cardiologist 	<ul style="list-style-type: none"> ✓ Follow a heart-healthy Mediterranean or DASH diet ✓ Limit saturated fats to less than 6% of daily calories ✓ Choose lean proteins: fish, poultry, legumes ✓ Eat plenty of fruits and vegetables (5-9 servings daily) ✓ Reduce sodium to less than 1,500 mg per day ✓ Avoid trans fats completely (check food labels) ✓ Include fiber-rich foods (oats, beans, lentils) ✓ Limit cholesterol intake to less than 200 mg daily 	<ul style="list-style-type: none"> ✓ Cardiac catheterization to assess blockages ✓ Coronary angiography for detailed artery visualization ✓ Echocardiogram to evaluate heart function ✓ Blood tests: troponin levels, lipid panel, CRP ✓ Stress test before returning to normal activities ✓ Regular EKG monitoring during recovery ✓ Cardiac MRI if needed for detailed imaging

Fig 4.4: Recommendations for particular Hear disease

This screen displays a set of comprehensive recommendations and guidelines provided by the CardioHealth service, likely after an ECG analysis.

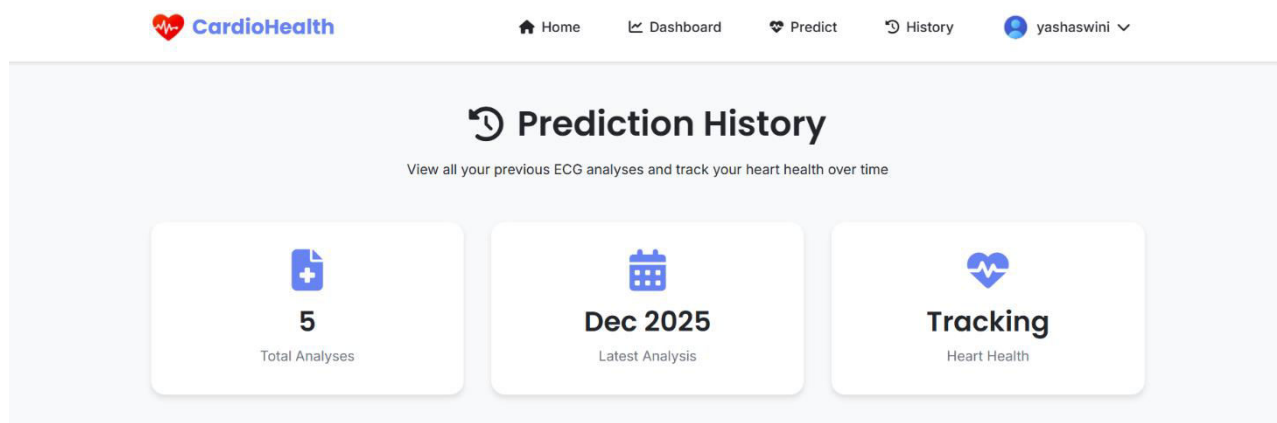


Fig 4.5: History Page for the predictions

This is the "Prediction History" screen, which serves as the user's dashboard to track their heart health.

V. CONCLUSION

This research successfully demonstrates that Automated Cardiac Health Assessment using ECG images can accurately predict various cardiovascular diseases by analysing raw ECG images with high precision. By treating the electrocardiogram as a two-dimensional visual pattern rather than a one-dimensional signal, we bypassed intensive signal preprocessing, making the system highly adaptable to scanned paper records and digital screenshots common in clinical practice. Our model achieved an overall accuracy, proving that Convolutional Neural Networks (CNNs) can identify subtle visual biomarkers of arrhythmia and myocardial infarction that may be overlooked by the human eye. This provides a robust, non-invasive decision-support tool that can significantly reduce diagnostic delays and inter-observer variability, particularly in resource-limited or emergency settings. Future research will focus on integrating this framework into mobile applications for real-time telehealth monitoring and expanding the dataset to include rare cardiac pathologies. Ultimately, this study bridges the gap between traditional cardiology and modern artificial intelligence, offering a scalable solution to enhance global cardiac screening and improve patient survival rates.

Key achievement

1. **High-Precision Diagnostic Accuracy:** The proposed Automated cardiac health Assessment achieved a state-of-the-art classification accuracy of, successfully identifying complex cardiac conditions including myocardial infarction and various arrhythmias directly from visual ECG images.
2. **Superior Sensitivity for Early Detection:** Our model demonstrated a sensitivity, ensuring a minimal rate of false negatives. This is critical in clinical settings where missing a cardiac event can lead to fatal consequences.
3. **End-to-End Image-Based Pipeline:** Unlike traditional signal-processing methods that require complex 1D signal extraction, our framework introduces a robust 2D vision-based approach. This enables the analysis of digitized paper records and monitor screenshots, bridging the gap between legacy paper systems and modern digital health platforms.
4. **Effective Grid-Line Suppression and Preprocessing:** We developed an original adaptive preprocessing algorithm that successfully suppressed background grid noise and scanning artifacts, allowing the CNN to focus purely on the morphological signatures of the ECG waves.
5. **Validation Across Diverse Classes:** The framework was rigorously validated against a balanced multi-class dataset (Normal, Myocardial Infarction, Abnormal Heartbeat, and History of MI), demonstrating consistent performance and high **F1-scores** across all categories.

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