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Web-Based System for Ecg Arrhythmia Detection and Heart Disease Prediction Using Deep Cnn

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***Abstract*—The increasing prevalence of cardiovascular diseases necessitates the development of efficient diagnostic tools to enhance early detection and management. This paper presents a web-based system designed for ECG arrhythmia detection and heart disease prediction utilizing Deep Convolutional Neural Networks (D-CNNs).We classify ECG in to 5 categories, one being normal and the others include, Atrial Fibrillation, Atrial Flutter,Ventricular Tachycardia, and Ventricular Fibrillation .The proposed system leverages a user- friendly interface to facilitate real-time ECG data upload and analysis, enabling both healthcare professionals and patients to monitor cardiac health effectively.**

The CNN model is trained on a diverse dataset comprising labelled ECG signals, allowing it to learn complex patterns associated with various arrhythmias and heart conditions. The system achieves high accuracy and sensitivity by using various algorithms, significantly outperforming traditional methods in both classification and prediction tasks. Additionally, the web-based platform ensures accessibility, enabling users to receive instant feedback and insights about their cardiac health from any location.

***Index Terms*—Electrocardiogram, Convolutional Neural Network, Atrial Fibrillation, Atrial Flutter, Ventricular Tachycardia, and Ventricular Fibrillation**

I. INTRODUCTION

Cardiovascular diseases (CVDs) remain the leading cause of death globally, accounting for millions of fatalities each year. Early diagnosis and timely treatment are critical to reducing the mortality and morbidity associated with these conditions. The electrocardiogram (ECG) is a widely utilized diagnostic tool for monitoring cardiac activity and identifying abnormalities such as arrhythmias. Despite its effectiveness, manual ECG analysis is often labor-intensive, requires expert interpretation, and is susceptible to human error, especially in emergency scenarios or when handling large datasets with the rise of artificial intelligence (AI) and deep learning, there is an increasing opportunity to revolutionize healthcare by automating complex diagnostic processes. Convolutional Neural Networks (CNNs), a subset of deep learning models, have shown exceptional performance in analyzing medical imaging and time-series data, making them an ideal choice for ECG signal processing. CNNs can automatically learn features from raw data, eliminating the need for extensive manual feature engineering, and achieve high accuracy in tasks such as arrhythmia classification and heart disease prediction.

This project proposes a web-based system for ECG arrhythmia detection and heart disease prediction using deep CNNs. The system is designed to provide a seamless, accurate, and efficient solution for automated ECG analysis. Key features of the system include:

Automated Arrhythmia Detection: The system leverages deep CNNs to classify various types of arrhythmias with high precision, aiding in the early diagnosis of potentially life-threatening

Heart Disease Prediction: Beyond arrhythmia detection, the system integrates predictive analytics to assess the risk of underlying heart diseases based on ECG patterns.

Web-Based Accessibility: The system is deployed as a web-based application, ensuring remote access for both healthcare professionals and patients, thereby improving accessibility and usability.

Heart Disease Prediction: Beyond arrhythmia detection, the system integrates predictive analytics analytics to assess the risk of underlying heart diseases based on ECG patterns.

Web-Based Accessibility: The system is deployed as a web-based application, ensuring remote access for both healthcare professionals and patients, thereby improving accessibility and usability.Real-Time Processing: Designed for efficiency, the system provides real-time analysis of ECG data, making it suitable for emergency scenarios and continuous monitoring.

Scalability and Usability: The system is built to handle large-scale data, making it adaptable for clinical settings and research applications.

By combining state-of-the-art deep learning techniques with an intuitive web interface, this system bridges the gap between advanced technology and practical healthcare applications. It empowers clinicians with reliable diagnostic tools, reduces their workload, and enhances the quality of patient care. Furthermore, it provides patients with a means to proactively monitor their heart health, enabling timely interventions and reducing the risk of complications.

The proposed system aims to address the challenges of traditional ECG analysis by offering an innovative, scalable, and user- friendly solution for automated arrhythmia detection and heart disease prediction. Through the integration of cutting-edge deep CNNs and web-based technology, this project aspires to contribute significantly to the advancement ofcardiovascular diagnostics and the improvement of global health outcomes. Arrhythmias are broken down into various types such as tachycardia, bradycardia, supraventricular tachycardia, atrial flutter, atrial fibrillation, etc. Classification is done based on beats per minute (BPM). It is broadly classified into three types.

These broad types are further classified into subtypes depending upon certain conditions.

Bradycardia- BPM<60

Normal heart- BPM is between 60 to 100.

Tachycardia- BPM>100. Bradycardia is divided into two types

1° heart block- In this situation, the PR wave is prolonged i.e., PR>200ms.

2° heart block- In this situation, PR and QRS complex occur alternatively. i.e., when PR>0, QRS =0, and when QRS>0, PR=0.

Tachycardia is further classified based on narrow and broad QRS complex.

Narrow complex- QRS<120ms. Broad complex- QRS>120ms.

Under narrow QRS complex, the following types are detected.

Normal sinus rhythm.

Supra ventricular tachycardia (SVT). Atrial fibrillation. Under broad QRS complex the following types are detected.

Monomorphic Ventricular Tachycardia (MVT). Polymorphic Ventricular Tachycardia (PVT). Ventricular Flutter.

The medical data of the patients is necessary for detection of heart disease because it contains unknown patterns which are essential for data analysis which is done using many algorithms and mathematical models. The healthcare sector has the vast amount of medical data, which is not excavated.

Many researchers have proposed many Machine learning algorithms to classify the cardiac arrhythmia. Right Bundle Branch Block (RBBB) and Left Bundle Branch Block (LBBB) are classified as a disruption in the normal system that produces an abnormal QRS shape. The right bundle adheres to the Right Ventricle (RV), and the right bundle does not produce any activation. This behaviour in the electrical aspect creates an abnormal QRS morphology. In the LBBB, the left bundle does not activate.

II. BACKGROUND STUDY

Many researchers have proposed many Machine learning algorithms to classify the cardiac arrhythmia using various techniques and methods, It enhanced their accuracy and model building for prediction by using advanced Deep Convolutional neural networks. Some of them used for model building and training are ResNet50: A residual network designed to handle vanishing gradient problems with deep layers, excelling in learning complex.

InceptionV3: Employs multi-scale feature extraction using inception modules, enhancing accuracy while reducing computational cost.

VGG16: A deep architecture with uniform kernel sizes (3×3) designed for high-resolution feature extraction.

The objective of this work is to create web-based platform to classify the given ECG data as belonging to either normal or abnormal (arrhythmia) category. Section 2 explicates proposed system with system architecture. Section 3 depicts results and comparison. At end, Section 4 shows conclusion with future work.

Upload functionality for ECG recordings (CSV, image, or raw signal formats) Prediction results with classifications (e.g., normal, atrial fibrillation, ventricular tachycardia, etc.). Historical analysis to track patient ECG trends over time. Export options (PDF reports or JSON data).

System Architecture

Frontend-Frameworks: Built using modern JavaScript frameworks like React, Vue.js, or Angular to ensure a dynamic and responsive user experience.

1. Web Based Cardiac Arrhythmia Classification System

Cardiovascular disease causes most of the deaths today. This web-based system helps to predict heart disease which make use of patient's ECG values related to heart disease. Medical dataset of the patients is used to extract the ECG values. In this paper, cardiac arrhythmia type is classified and predicted using machine learning algorithms

The web application acts as a bridge between the deep learning models and the end-users, such as clinicians, researchers, or even patients. It is designed to facilitate real- time ECG arrhythmia prediction and provide a user-friendly interface for diagnostics and visualization. The application is scalable, secure, and accessible via desktop and mobile devices.

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Back-End-Frameworks: Implemented using Django or Flask for Python integration with deep learning models. Alternatively, Node.js for a non-blocking, event-driven architecture.

APIs: RESTful APIs or GraphQL endpoints to handle requests such as ECG uploads, predictions, and fetching historical data

III. MODEL DEPLOYMENT

Integration of Deep Learning Models: Models are exported as ONNX or TensorFlow SavedModel formats for optimized inference. Deployed using TensorFlow Serving.

Inference Optimization: Utilize GPU-based or TPU-based computation for real-time predictions. Implement batch processing for multiple requests.

- Train the deep learning models (ResNet50)

MobileNetV2 is a convolutional neural network architecture optimized for mobile and embedded vision applications. It improves upon the original MobileNet by introducing inverted residual blocks and linear bottlenecks, resulting in higher accuracy and speed while maintaining low computational costs.

MobileNetV2 is widely used for tasks like image classification, object detection, and semantic segmentation on mobile and edge devices.

Key Features of MobileNet V2

Inverted Residuals: One of the most notable features of MobileNet V2 is the use of inverted residual blocks. Unlike traditional residual blocks that connect layers of the same depth, inverted residuals connect layers with different depths, allowing for more efficient information flow and reducing computational complexity.

Linear Bottlenecks: MobileNet V2 introduces linear bottlenecks between the layers. These bottlenecks help preserve the information by maintaining low-dimensional representations, which minimizes information loss and improves the overall accuracy of the model.

Depth wise Separable Convolutions: Similar to MobileNet V1, MobileNet V2 employs depth wise separable convolutions to reduce the number of parameters and computations. This technique splits the convolution into two separate operations: depth wise convolution and pointwise convolution, significantly reducing computational cost. ReLU6 Activation Function: MobileNet V2 uses the ReLU6 activation function, which clips the ReLU output at 6. This helps prevent numerical instability in low-precision computations, making the model more suitable for mobile and embedded devices. Architecture of MobileNet V2

The MobileNet V2 architecture is designed to provide high performance while maintaining efficiency for mobile and

embedded applications. Below, we break down the architecture in detail, using the schematic of the MobileNet V2 structure as a reference.

during training, data goes through forward pass, then loss function is computed and to reduce the loss, weights of neuron are updated in backward pass.

Convolutional networks have its root from biology and mathematics. Convolutional networks are variations of multilayer perceptron (MLP).

In Convolution layer, a kernel/filter is used which defines weights for input image pixels. Convolution operation is performed in convolution layer where the dot product of input image pixel values and weight defined by filter is ca right and top to bottom to cover each overlapping part. At end of this layer, a smaller convolution matrix is generated which represent the results of convolution operation.

The convolution matrix passed through activation function to introduce nonlinearity. In proposed system, Rectifier Linear Units (ReLu) is used as activation function which allows the network to train itself through backpropagation. The size of convolution matrix is further reduced by down sampling in Pooling layer. Here a filter is again passed over the previous matrix

known for its simplicity and depth, effectively captured critical features from ECG signals, resulting in [mention key performance metrics such as accuracy, sensitivity, precision, etc.].

IV. SYSTEM ARCHITECHTURE

Frontend-Frameworks: Built using modern JavaScript frameworks like React, Vue.js, or Angular to ensure a dynamic and responsive user experience.

Upload functionality for ECG recordings (CSV, image, or raw signal formats) Prediction results with classifications (e.g., normal, atrial fibrillation, ventricular tachycardia, etc.). Historic analysis to track patient ECG trends over time. Export options (PDF reports or JSON data).

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V. EXPERIMENTS AND RESULTS

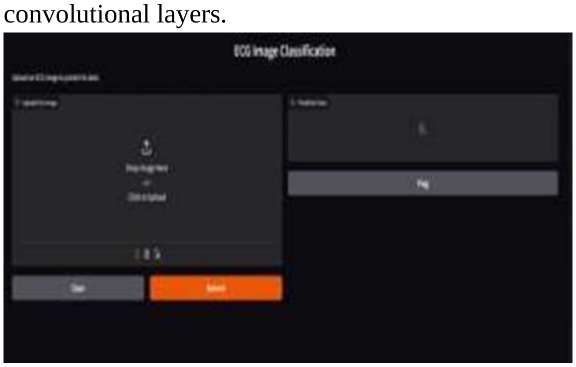
In a web-based system for ECG arrhythmia and heart disease prediction using deep convolutional neural networks (CNNs) and algorithms like ResNet50, VGG16, and Inception V3, the evaluation metrics and result interpretation play a crucial role in determining the model's effectiveness.

Such a system typically processes ECG signals to classify different types of arrhythmias or detect abnormalities indicative of heart disease. Evaluation metrics like accuracy, precision, recall (sensitivity), specificity, and F1-score are commonly employed to measure the system's performance. For imbalanced datasets, metrics such as the area under the Receiver Operating Characteristic (ROC) curve (AUC-ROC) and confusion matrix analysis provide deeper insights into

the model's prediction capabilities. These metrics help assess the models' ability to distinguish between classes effectively. Additionally, comparative performance across architectures like ResNet50, VGG16, and Inception V3 is analyzed to identify the most efficient model for deployment. Robust results in such systems demonstrate high accuracy and low false positive/false negative rates, making the solution reliable for real-world applications in clinical environments.

Overview of the Web-Based ECG Arrhythmia Prediction SystemThe web-based system for ECG arrhythmia and heart disease prediction utilizes advanced deep learning architectures such as ResNet50, VGG16, and Inception V3 to classify ECG signals. These models are trained on labeled ECG datasets to detect arrhythmias and other heart conditions. The system's performance is evaluated using several key metrics to ensure accuracy, reliability, and clinical applicability.

Key Evaluation Metrics
Results and Comparative Analysis
ResNet50: Known for its deep residual learning, excels in feature extraction but may have slightly higher computational requirements.
VGG16: Simplifies implementation but might underperform in handling complex ECG variations compared to ResNet50.
Inception V3: Offers a balance of computational efficiency and high accuracy due to its mixed convolutional layers.



By evaluating these metrics, the most suitable architecture is identified for real-time deployment, ensuring the system provides reliable predictions for arrhythmia and heart disease detection.

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