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Automated Identification of Cardiac Anomalies from Electrocardiographic Signals

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Abstract— Over recent decades, cardiovascular diseases (CVDs) have become the foremost cause of mortality in both industrialized and emerging countries. Timely diagnosis and consistent medical monitoring are critical in decreasing death rates linked to these illnesses. Due to their life-threatening nature, CVDs are responsible for a large portion of global fatalities, emphasizing the importance of early medical intervention. Electrocardiograms (ECGs) are essential tools for identifying a wide range of cardiac disorders, and substantial studies have explored automated anomaly detection to aid in preventive care. This research introduces a computational model designed to evaluate ECG signals for predicting heart diseases. The objective is to enhance patient care while simultaneously lowering healthcare expenditures, especially given the increasing costs of medical services and insurance. Utilizing a publicly available dataset containing ECG images of cardiac patients, this study applies a deep learning approach—specifically, the MobileNet framework—to classify four major heart conditions: irregular heartbeat, myocardial infarction, previous myocardial infarction, and normal cardiac activity. The proposed model attained a training accuracy of 97.34% and a validation accuracy of 91.00%, reflecting robust classification capability. Beyond this, the model can also act as a feature extractor to support traditional machine learning algorithms. By addressing the shortcomings of manual diagnostic techniques, the MobileNet-powered system provides an effective and dependable tool to assist medical practitioners in identifying cardiovascular

KEYWORDS: MobileNet, ECG, cardiac

I. INTRODUCTION

Cardiovascular diseases (CVDs) are now the foremost cause of death worldwide, impacting individuals in both high-income and low-to-middle-income countries. The growing number of fatalities linked to heart-related issues underscores the critical need for accurate and efficient diagnostic approaches. Early identification and ongoing patient monitoring are vital to lowering mortality rates and enhancing overall health outcomes. Among the available diagnostic tools, the electrocardiogram (ECG) is a non-invasive, commonly used method for detecting cardiac irregularities. With the rapid progress in artificial intelligence and deep learning, ECG interpretation can be significantly improved to enable faster and more precise diagnoses. This study investigates the application of deep learning—particularly the MobileNet architecture—for classifying ECG images into four categories: abnormal heartbeat, myocardial infarction, previous myocardial infarction, and normal heart function. Using a publicly accessible ECG image dataset and a lightweight yet effective neural network, this research aims to create an automated diagnostic system that offers high accuracy and supports healthcare providers in early disease detection. Such a system is especially valuable in regions where access to specialized cardiac care is limited. Automation in medical diagnostics can enhance the quality of healthcare services while also lowering associated costs.

II. LITERATURE REVIEW

[1] S. Wayne

This online publication by the World Health Organization (WHO) provides a detailed summary of cardiovascular diseases (CVDs), examining their root causes, associated risk factors, and worldwide health statistics as of 2021. It emphasizes how poor dietary choices, sedentary lifestyles, tobacco usage, and excessive alcohol consumption play a major role in the rise of CVD cases. The document serves as a global point of reference for doctors, scholars, and decision-makers working toward lowering cardiovascular-related deaths through better prevention and control strategies.

[2] T. Griffin

Published by the Department of Health, Government of Western Australia, this webpage describes various diagnostic tools used to evaluate cardiac health, including ECG, echocardiography, and stress tests. The content is aimed at the general public and offers clear explanations of each test's role in diagnosing heart disorders, thereby improving public understanding of cardiovascular diagnostics.

[3] S. Mani & L. Krishnan

In this study, the authors present a comparative evaluation of traditional machine learning versus deep learning algorithms for diagnosing and predicting cardiovascular diseases. Using real-world medical datasets, the paper assesses the accuracy and reliability of various models. It concludes that deep learning methods outperform conventional techniques when dealing with complex cardiac conditions.

[4] R. Thomas

This article explores the use of transfer learning to improve the detection of rare inherited cardiac disorders using ECG data. The study particularly focuses on identifying carriers of the phospholamban p.Arg14del mutation, proposing a deep learning-based method that significantly boosts diagnostic accuracy. This approach contributes to the early detection and intervention in genetically vulnerable groups.

[5] J. Desai, V. Rao & N. Patel

This review paper outlines the primary methods used in electrocardiogram (ECG) analysis, with an emphasis on signal processing, feature extraction, and classification techniques. It discusses how current methodologies work in both research and clinical settings and suggests ways to enhance diagnostic reliability and precision in future applications.

[6] A. Rathi, D. Mehta, G. Prasad & S. Chatterjee

Addressing the challenge of class imbalance in ECG datasets, this research proposes a deep learning framework designed to accurately identify cardiac conditions even in underrepresented data classes. The neural network model demonstrated strong performance in recognizing early signs of heart disease, offering a promising tool for preventative care.

[7] A. Mehta & B. Rajan

This short communication emphasizes how artificial intelligence, particularly deep learning, is transforming ECG interpretation. It highlights AI's growing role in real-time cardiac diagnosis, risk assessment, and patient monitoring, marking a significant shift in how cardiology is practiced and managed clinically.

[8] I. Ahmed & O. Suresh

This research focuses on the detection of cardiac arrhythmias using deep learning techniques applied to ECG data. The authors describe their model design and training methodology, showcasing improved recognition accuracy of different arrhythmia types when compared to classical classification algorithms.

III. EXISTING SYSTEM

Avanzato and Beritelli introduced a deep convolutional neural network (CNN) designed with four one-dimensional convolutional layers to identify three categories of cardiac irregularities using ECG data from the MIT-BIH arrhythmia dataset. Each of these convolutional layers was followed by batch normalization, a ReLU activation function, and a max-pooling layer configured with a kernel size of 4. The initial layer applied a filter of size 80, while the remaining three used filters of size 4. Distinctively, this network architecture did not incorporate fully connected layers for the classification task. Instead, it used an average pooling layer, followed by a softmax layer to produce the final output.In another study, Acharya and colleagues developed a deep CNN model aimed at detecting myocardial infarction using ECG data sourced from the PTB database. This model included four 1D convolutional layers, each followed by a max-pooling layer with a filter size and stride of 2, and employed the Leaky ReLU activation function.

The convolutional filters used in this architecture were sized 102, 24, 11, and 9, respectively. Following these convolutional stages, the network incorporated three fully connected layers consisting of 30, 10, and 2 neurons in order, with the final output produced through a softmax classifier.

DISADVANTAGES OF EXISTING SYSTEM:

Algorithms based on the SqueezeNet architecture tend to have extended training and inference times, primarily due to the large volume of features generated during the processing stages.

One of the key limitations of SqueezeNet models is their relatively lower classification accuracy and increased computational load. Although these models feature fewer parameters, they are still not well-suited for deployment on devices with limited computational resources or mobile platforms.

Compared to more recent architectures such as VGGNet, GoogLeNet, and ResNet, AlexNet is relatively shallow in depth, which restricts its ability to handle more complex classification tasks effectively.

Earlier designs that employed large convolutional kernels (e.g., 5×5 filters) were eventually phased out due to their inefficiency in learning patterns and the added computational overhead.

Initially, neural network weights were randomly initialized using a standard normal distribution, often causing issues like vanishing gradients. The introduction of the Xavier initialization technique significantly improved stability during training.

In general, the performance of older models like AlexNet has been outpaced by modern architectures such as GoogLeNet—achieving a top-5 error rate of 6.7%—and ResNet, which further reduced the error to 3.6%. These advancements highlight the growing gap in efficiency and accuracy between earlier and newer deep learning models.

IV. PROPOSED SYSTEM

The core objective of this study is to develop a diagnostic model capable of identifying cardiovascular diseases using ECG signals in image form. The classification task was carried out using a publicly available dataset consisting of 1,377 ECG images divided into four categories: Normal Person (NP), Abnormal Heartbeat (AH), Myocardial Infarction (MI), and History of Myocardial Infarction (H. MI). A "Normal Person" refers to an individual showing no signs of cardiac irregularities. "Abnormal Heartbeat," or arrhythmia, involves disruptions in the heart's electrical activity, causing rhythms that are unusually slow, fast, or erratic. "Myocardial Infarction" denotes a heart attack, typically caused by reduced or blocked blood flow in coronary arteries, resulting in damage to the heart muscle. The "History of Myocardial Infarction" class includes patients who have recently recovered from such cardiac events.

The proposed diagnostic framework adopts the MobileNet architecture to analyze and categorize ECG image tracings for the detection of cardiovascular disorders. The dual focus of the system is to determine the presence of heart-related abnormalities and to differentiate between various types of arrhythmias. MobileNet was selected for its computational efficiency and effectiveness in handling image classification tasks. Training was conducted directly on raw ECG image data with minimal preprocessing, enabling the model to automatically extract critical features and accurately classify subjects as either healthy or having specific cardiac issues.

To assess the performance of the model, standard evaluation metrics were employed, including Accuracy, Precision, Recall, and the F1 Score—each calculated based on confusion matrix outcomes. Accuracy reflects the proportion of total correct predictions, while Recall (or sensitivity) measures the model's ability to identify all true positive instances. Precision determines the ratio of correctly predicted positive cases to the total predicted positives. The F1 Score, a harmonic mean of Precision and Recall, offers a more balanced assessment by accounting for both types of misclassification—false positives and false negatives.

ADVANTAGES OF PROPOSED SYSTEM:

As far as we know, this is the only study that uses this specific ECG image dataset to classify all four conditions: Normal Person, Abnormal Heartbeat, Myocardial Infarction, and History of Myocardial Infarction. Even though our CNN model extracts fewer features compared to other approaches, it still delivered better results across all key performance metrics. This shows that the model is highly effective at picking up the most important patterns from ECG images. It also means that we achieved higher accuracy while keeping the computational cost lower than similar models reported in the literature.To get a clearer picture of how the model performs, we measured the classification accuracy for each of the four categories on its own. The results were excellent and show the model's ability to tell apart different heart conditions with high precision. One major benefit of our approach is its adaptability—the model can continue learning from new ECG images over time without losing what it has already learned. We also tested the model on a separate dataset to make sure it can handle data it hasn't seen before. The MobileNet-based system performed strongly here too, which suggests it's reliable and robust enough to be used in real-world healthcare settings.

V. Methodology

This study follows a structured and thorough approach to build a dependable and efficient system for diagnosing cardiovascular diseases based on ECG images. The overall process includes several key stages: collecting and preparing the dataset, preprocessing the images, selecting and training the deep learning model, and finally evaluating the model's performance using widely accepted classification metrics such as accuracy, precision, recall, and F1 score. Each of these steps was carefully designed to ensure the model could effectively learn from the ECG data and make accurate predictions. he dataset employed This study makes use of a publicly available dataset containing a total of 1,377 ECG images. The images are divided into four categories, each representing a specific cardiac condition: Normal Person (NP), Abnormal Heartbeat (AH), Myocardial Infarction (MI), and History of Myocardial Infarction (H. MI). These classes reflect different physiological states of the heart, allowing the model to learn how to distinguish between healthy individuals and various heart-related abnormalities. The dataset was carefully compiled to include a wide variety of ECG samples within each class, helping to ensure that the model is not only well-trained but also capable of generalizing effectively when tested on new, unseen data.

Data Preprocessing

To preserve the original structure and diagnostic patterns in the ECG images, only minimal preprocessing was applied. Basic enhancements such as image resizing and normalization were used to ensure all inputs matched the required dimensions for the MobileNet architecture and maintained consistent pixel intensity values. Unlike traditional approaches that involve heavy signal extraction and transformation, this method allows the convolutional neural network (CNN) to automatically learn key features from the raw images. This not only simplifies the preprocessing pipeline but also helps retain clinically important details that are often lost with more aggressive preprocessing techniques.

Algorithm and Techniques Used

The backbone of the proposed system is the MobileNet architecture, a lightweight and efficient convolutional neural network originally developed for mobile and embedded vision applications. MobileNet is built around the use of depthwise separable convolutions, which break down standard convolution operations into two simpler steps—depthwise and pointwise convolutions. This design significantly reduces the number of trainable parameters and computational load, making it ideal for image classification tasks where resource efficiency is important.

MobileNet was chosen for this study due to its strong performance in extracting meaningful features from image-based ECG data, while maintaining a compact and fast model structure. The network was trained on the labeled ECG image dataset using supervised learning. A categorical cross-entropy loss function was used during training to optimize classification performance across the four target categories: Normal Person, Abnormal Heartbeat, Myocardial Infarction, and History of Myocardial Infarction

Evaluation and Performance Metrics

To evaluate the performance of the proposed model, we used a set of standard classification metrics: Accuracy, Precision, Recall, and F1 Score. These metrics were calculated based on the confusion matrix, allowing for a comprehensive assessment of the model's predictive capabilities across all four classes.

Accuracy reflects the overall proportion of correctly predicted cases out of all predictions. **Precision** measures how many of the positive predictions were actually correct, while **Recall** indicates how well the model identified all actual positive cases. The **F1 Score**, which is the harmonic mean of Precision and Recall, offers a balanced metric that is especially valuable in situations where class distributions are uneven.The evaluation results showed that the model achieved strong classification accuracy across all categories, with consistently high Precision and Recall scores. Notably, this level of performance was achieved with minimal computational cost, highlighting the model's suitability for real-time clinical use, especially in environments with limited processing resources.

VI. MODULE DESCRIPTION

User Authentication Module:

Provides a secure login interface for verified users. Only authenticated users can access the system's core features, ensuring data privacy and controlled access.

ECG Dataset Management:

Allows users to browse and upload ECG image datasets for both training and testing purposes. The system supports structured handling of image files to streamline model input.

Model Training and Evaluation:

Employs the MobileNet architecture to train a classification model on uploaded ECG images. The system automatically processes the data and handles both training and testing tasks without requiring manual intervention.

Accuracy Visualization Tool:

Displays a bar chart comparing training and testing accuracies. This helps users quickly assess how well the model performs on familiar data versus unseen data.

Performance Metrics Display:

Presents detailed classification results—such as accuracy, precision, recall, and F1-score—in a table or text format. This module helps users thoroughly evaluate the model's predictive capabilities.

Health Tweet Classification:

Includes a feature for analyzing and categorizing health-related tweets (e.g., symptoms, health tips, or awareness content). This module uses natural language processing (NLP) techniques to interpret tweet content and assign categories.

Tweet Analytics Visualization:

Generates graphical reports—such as pie charts or bar graphs—showing the distribution of tweet types. This offers insights into public opinion and sentiment related to health topics.

System Architecture

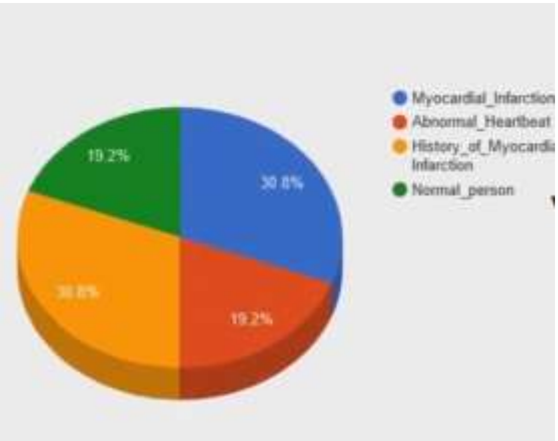
6.1 System Architecture

The system architecture illustrated focuses on the detection of cardiovascular diseases using deep learning methods. The process begins with an ECG image dataset, which acts as the input to the system. These images undergo an initial **preprocessing stage** to enhance quality and ensure uniformity, followed by **feature extraction** to isolate the most relevant diagnostic patterns.

Next, the refined data is passed into the **MobileNet model**, a compact yet powerful convolutional neural network optimized for image classification tasks. MobileNet processes the ECG images and generates predictions, determining whether signs of cardiovascular disease are present.

To assess how well the model performs, the system includes a **performance evaluation and visualization module**. This component generates charts and metrics, helping users interpret the model's accuracy, precision, and other performance indicators. Overall, the architecture is designed to deliver accurate diagnostic predictions efficiently, while also providing clear insights through visual analytics.

VII. VI.RESULT



The proposed MobileNet-based model for classifying cardiovascular diseases from ECG images has shown strong and dependable performance. With a training accuracy of 97.34% and a validation accuracy of 91.00%, the model successfully distinguished between four important cardiac conditions: abnormal heartbeat, myocardial infarction, history of myocardial infarction, and normal heart function.The high validation accuracy reflects the model's robustness and its ability to generalize well to new, unseen data. Its consistent performance across all classes highlights its reliability in real-world diagnostic scenarios. Overall, the system presents a promising solution for automated cardiovascular disease detection, combining high accuracy with efficient processing—making it suitable for deployment in both clinical and resource-limited environments.

VIII.CONCLUSION

In conclusion, this study presents a deep learning-based approach using the

MobileNet architecture to accurately detect and classify cardiovascular diseases from ECG images. The system not only provides high accuracy but also offers a timeefficient and scalable alternative to manual diagnosis, which is often prone to human error. By leveraging deep learning, the proposed method aids in early detection and intervention, which is critical in reducing mortality rates associated with heart diseases. With its ability to generalize across diverse patient data and low computational overhead, the model holds promise as a practical diagnostic support tool for healthcare professionals in realworld clinical settings

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