Automated Heart Disease Detection from ECG Signals using a Hybrid Deep Learning Approach

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Abstract:

Cardiovascular diseases remain one of the leading causes of mortality worldwide, making early and accurate diagnosis critically important. Electrocardiogram (ECG) signals are widely used for detecting heart-related abnormalities; however, manual interpretation is time- consuming and prone to human error. This research proposes an automated ECG classification system using advanced deep learning models including Convolutional Neural Networks (CNN), MobileNet, DenseNet, and a hybrid MobileNet + LSTM model. The system classifies ECG images into four categories: myocardial infarction, history of myocardial infarction, abnormal heartbeat, and normal heart conditions. Experimental results indicate that the hybrid model outperforms individual models by effectively capturing both spatial and temporal features. The proposed system demonstrates high accuracy and reliability, making it suitable for real- world clinical applications.

Keywords:

ECG Classification, Deep Learning, CNN, MobileNet, DenseNet, LSTM, Heart Disease Detection

1. Introduction

Heart diseases are the major
global health concern responsible for millions of deaths every year. Early diagnosis plays a key role in reducing mortality rates. ECG signals provide essential insights into heart activity , but interpreting them manually requires expertise and can lead to inconsistencies. With advancements in artificial intelligence, automated systems can assist doctors in analyzing ECG data more efficiently. This research focuses on the developing a deep learning based system that can automatically classify ECG signals with high accuracy . Unlike traditional approaches, this system leverages multiple deep learning architectures and compare their performance to identify the most effective model.

1.1 Motivation :

The motivation for this research stems from the rapidly increasing prevalence of cardiovascular disease worldwide, which remain one of the leading causes of mortality . Early detection and accurate diagnosis are critical in reducing the risk of severe complications and improving patient outcomes. However, traditional ECG analysis relies heavily on manual interpretation by medical experts , which is not only time consuming but also prone to human error , especially when dealing with complex or subtle waveform variations. With the growing demand for faster and more reliable diagnostic systems, there is a strong develop automated solutions that can assist healthcare professionals. In recent years, artificial intelligence and deep learning have shown significant potential in transforming medical diagnostics by enabling high-speed and accurate analysis of medical data. This project is motivated by the need to bridge the gap between conventional medical diagnosis and intelligent automated by leverage advanced deep learning techniques for ECG classification.

1.2 Problem Statement:

Accurate classification of ECG signals presents several challenges due to the inherent complexity of cardiac waveforms and variability in patient data. ECG signals often contain subtle patterns that are difficult to interpret, even for experienced clinicians. Additionally, variations in signal quality, noise interference, and differences in patient conditions further complicate the analysis process. Traditional machine learning approaches rely on handcrafted features, which require domain expertise and often fail to capture the full complexity of ECG signals. These models also struggle to generalize across different datasets, limiting their effectiveness in real-world scenarios. Furthermore, the presence of noise and signal distortion can significantly degrade model performance. To address these challenges , this research proposes a hybrid deep learning approach that combines the strengths of multiple architectures. By leveraging both spatial and temporal feature extraction, the proposed system aims to improve classification accuracy , robustness, and generalization capability.

1.3 Objectives

The primary objective of this research is to develop an efficient and reliable automated system for ECG classification using deep learning techniques. The system aims to accurately categorize ECG signals into clinically relevant classes, thereby assisting healthcare professionals in diagnosis. A key objective is to perform a comparative analysis of different deep learning models, including Convolutional Neural Networks (CNN), MobileNet and DenseNet to evaluate their performance in ECG classification tasks. Additionally, this study focuses on implementing a hybrid model that combines MobileNet with long Short Term Memory (LSTM) networks to capture both spatial and temporal features effectively. Another important objective is to improve the overall accuracy and reliability of ECG classification by addressing limitations in existing models. The research also aims to develop a scalable and efficient system that can be extended for real-world healthcare applications, enabling faster and more accurate diagnosis of cardiac conditions.

2. Literature Review:

Several studies have explored
the application of deep learning techniques for ECG signal classification, highlighting potential of these methods in improving diagnostic accuracy. Convolutional Neural Networks(CNNs) have been widely used due to their ability to automatically extract spatial features fromECGsignals, eliminating the need for manual feature engineering, Similarly Recurrent Neural Networks (RNNs), particularly Long Short- Term Memory (LSTM) models, have benn effective in capturing temporal dependencies within sequential ECG data. Recent research has shown that hybrid models, which combine CNN aand LSTM architectures achive superior performances by leveraging both spatial and temporal imformation these models prove a more comprehensive understanding of ECG signals, leading to improved classification accuracy, many existing systems still face limitations such as poor generalization across diverse, lack of real-time processing capabilities, and reduced accuracy when handling

multiple cardiac conditions. This research addresses these challenges by integratingmultiple deeplearning architectures into a unified frameworks, therebyenchancingperformance and reliability.

3. System Architecture:

The proposed system is designed using a modular architecture that integrates multiple components to ensure efficient processing and accurate classification of ECG signals. The architecture consists of several layers, each responsible for a specific function within the system.

3.1 Data Input Layer:

The data input layer is responsible for acquiring ECG images from the dataset. These images serve as the primary input for the system and are prepared.

3.2 Preprocessing layer:

In this layer, the input ECG image undergo preprocessing to ensure consistency and improve model performance. The images are resized to a standard dimension of 224×224 pixels, normalized to scale pixel values, and augmented using various techniques to increase dataset diversity and reduce overfitting.

3.3 Feature Extraction Layer:

MobileNet is employed as a feature extractor in this system due to its efficiency and lightweight architecture. It extracts meaningful spatial features from ECG images, which are essential for accurate classification.

3.4. Implementation:

The implementation of the proposed system is carried out using modern programming tools and deep learning frameworks. Python is used as the primary programming language due to its extensive support for machine learning libraries. TensorFlow and Keras are utilized for building and training deep learning models, while libraries such as NumPy, Pandas, and Scikit-learn are used for data processing and evaluation.The system is divided into multiple modules to ensure smooth operation. The user interface module allows users to upload ECG images for analysis. The backend processing module handles data preprocessing and model inference. The classification module predicts the category of the ECG signal using trained models, and the result is displayed to the user in an intuitive format. This modular implementation ensures scalability, maintainability, and ease of integration with real-world healthcare systems.The performance of the proposed system was evaluated using multiple deep learning models, including Convolutional Neural Networks (CNN), MobileNet, DenseNet, and a hybrid MobileNet + LSTM model. Each model was trained and tested on the ECG image dataset, and their performance was assessed using accuracy as the primary evaluation metric. The experimental results indicate that the CNN model achieved an accuracy of **82.75%**, demonstrating its effectiveness in extracting spatial features from ECG images MobileNET, known for its lightweight architecture and capturing deeper feature representations, recorded a comparatively lower accuracy of **75.88%**, which may be attributed to overfitting or the complexity of ECG patterns in the dataset.The hybrid MobileNet LSTM model outperformed all other models, achieving the highest accuracy of **92.99%**. This significant improvement highlights the advantage of combining spatial and temporal feature extraction techniques. MobileNet effectively captures spatial patterns in ECG images, while the LSTM component processes sequential dependencies, enabling the model to understand temporal variations in cardiac signals. This combination allows the hybrid model to detect subtle abnormalities that may not be captured by standalone architectures.hybrid model enhanced the system's ability to learn temporal relationships, which are crucial for ECG signal interpretation. Overall, the results clearly demonstrate that the hybrid model provides superior performance in terms of accuracy and reliability. Its ability to integrate both spatial and temporal information makes it highly suitable for real-world healthcare applications, where precise and timely diagnosis is essential. Therefore, the hybrid MobileNet + LSTM model can be considered the most effective approach for automated ECG classification in this study.The performance of the proposed system was evaluated using multiple deep learning models, including Convolutional Neural Networks (CNN), MobileNet, DenseNet, and a hybrid MobileNet + LSTM model. Each model was trained and tested on the ECG image dataset, and their performance was assessed using accuracy as the primary evaluation metric. The experimental results indicate that the CNN model achieved an accuracy of **82.75%**, demonstrating its effectiveness in extracting spatial features from ECG images MobileNET, known for its lightweight architecture andcapturing deeper feature representations, recorded a comparatively lower accuracy of **75.88%**, which may be attributed to overfitting or the complexity of ECG patterns in the dataset.

4. Results and Discussion

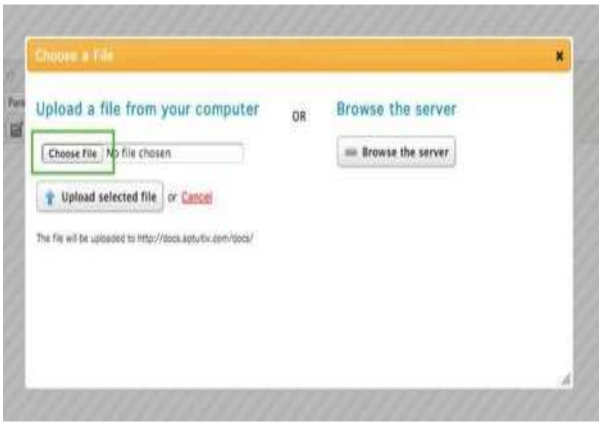
The performance of the proposed system was evaluated using multiple deep learning models, including Convolution Neural Networks (CNN), MobileNet, DenseNet, and a hybrid MobileNet + LSTM model. Each model was trained and tested on the ECG image dataset, and their performance was assessed using accuracy as primary evaluation metric. The experimental results indicate that the CNN model achieved an accuracy of 82.75%, demonstrating its effectiveness in extracting spatial features from ECG images MobileNet, known for its lightweight architecture and capturing deeper feature representations, recorded a comparatively lower accuracy of 75.88%, which may be attributed to overfitting or the complexity of EC patterns in the dataset. The hybrid MobileNet + LSTM model outperformed all other models, achieving the highest accuracy of 92.99%. This significant improvement highlight the advantage of combining spatial and temporal feature extraction techniques. MobileNet effectively captures spatial patterns in ECG images, while the LSTM componrnt processes sequential dependencies, enabling the model to understand temporal variations in cardiac signals. This combination allows the hybrid model to detect subtle abnormalities that may not be captured by standalone architectures. Further analysis shows that CNN performed better than DenseNet in this specific application, likely due to its simpler architecture and better adaptability to the dataset. MobileNet provided efficient feature extraction with reduced computational cost, making it a practical choice for deployment in real-world systems. The inclusion of LSTM in the hybrid model enhanced the system's ability to learn temporal relationships, which are crucial for ECG signals interpretation. Overall the results clearly demonstrate that the hybrid model provides superior performance in terms of accuracy and reliability. Its ability to integrate both spatial and temporal information makes it highly suitable for real-world healthcare applications, where precise and timely diagnosis is essential. Therefore, the hybrid MobileNet + LSTM model can be considered the most effective approach for automated classification in this study. The performance of the proposed system was evaluated using multiple deep learning models, including Convolution Neural Networks (CNN), MobileNet, DenseNet, and a hybrid MobileNet + LSTM model. Each model was trained and tested on the ECG image dataset

5. System Output:

- Login page:

- Home page:

- Upload page:



These demonstrate:

- User-friendly interface
- Real-time prediction
- Easy navigation

6. Limitation

Despite its advantages, the proposed system has certain limitations that need to be considered. One of the primary challenges is the requirement for a large and diverse dataset. Deep learning models generally perform better when trained on extensive datasets, and limited data can affect the model's ability to generalize across different patient conditions. Another limitation is the high computational cost associated with training deep learning models. The use of multiple architectures, especially hybrid models, requires significant processing power and memory, which may not be readily available in all environments. The current system is also limited to ECG image-based classification, which means it does not directly process raw ECG signal data or multi- lead inputs. This restricts its applicability in more advanced clinical scenarios. Furthermore, the system is not yet clinically deployed, meaning it still requires validation and approval before being used in real-world healthcare settings.

7. Future Enhancement:

To overcome the current limitations and improve the system further, several enhancements can be considered in future work. One important direction is the integration of multi-lead ECG data, which can provide more comprehensive information about cardiac activity and improve classification, accuracy. Another promising enhancement is cloud-based deployment, which would allow the system to be accused remotedly and handle large- scale data efficiently.

This would also reduce the need for high-end local hardware. Additionally, developing a mobile application can make the system more accessible to healthcare professionals, especially in remote or rural areas. In corporating Explainable AI (XAI) techniques is another crucial improvement. This would allow the system to provide clear explanations for its predictions, increasing trust and transparency among medical practitioners. Finally, integrating the system with hospital management systems can streamline workflows and enable seamless data sharing, making the solution more practical for real-world applications.

8. Conclusion:

In conclusion, this research demonstrates the effectiveness of deep learning techniques in the classification of ECG signals for detecting heart diseases. By comparing multiple models, including CNN, MobileNet and DenseNet, the study highlights the superior performance of the hybrid MobileNet + LSTM model. This model successfully combines spatial features extraction with temporal pattern recognition, resulting in improved accuracy and reliability. The proposed system not only enhances diagnostic accuracy but also reduces the burden on healthcare professionals by automating the analysis process. Its ability to deliver fast and consistent results makes it a valuable tool for supporting clinical decision-making. Although there are certain limitations, the system shows strong potential for real- world implementation with further improvements and validation. Overall this work represents a meaningful step toward the development of intelligent healthcare solutions, where artificial intelligence can assist doctors in providing faster, more accurate, and more efficient patient care.

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