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ECG Signal Classification for Arrhythmia Detection Using AI Approach

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Abstract - *This project aims to detect heart abnormalities from ECG signals using deep learning. An ECG records the electrical activity of the heart and helps in diagnosing arrhythmia. Traditional ECG analysis methods are slow and need manual interpretation .We use a 1D Convolutional Neural Network (CNN) to automatically classify ECG signals .The dataset used is the MIT-BIH Arrhythmia Database from PhysioNet. ECG signals are filtered to remove noise and normalized before training. The CNN model learns important heartbeat patterns directly from the data. We evaluate the model using accuracy precision, recall, and F1-score.A simple GUI is built using Streamlit to visualize ECG and show predictions .This system can help doctors in early and faster detection of heart diseases. The model is trained and tested on real ECG samples to ensure reliable performance .It achieves high accuracy in distinguishing normal and abnormal heartbeats. This project demonstrates the power of AI in medical signal analysis. Future improvements can include real time ECG monitoring using IoT devices..*

***Key Words:* ECG Signals, ECG Analysis,Physionet, Deep Learning , F1-score,Streamlit.**

1. INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) has significantly transformed the healthcare industry by enabling intelligent systems for disease detection and diagnosis. In recent years, AI-based models have been widely used to analyze biomedical signals such as Electrocardiogram(ECG) and Electroencephalogram (EEG), which provide valuable insights into heart and brain activities. These technologies have improved the accuracy and efficiency of medical diagnosis, supporting healthcare professionals in making informed decisions..

ECG is a widely used diagnostic tool that records the electrical activity of the heart and helps in identifying cardiovascular conditions such as arrhythmias, heart attacks, and other abnormalities. Similarly, EEG measures the electrical activity of the brain and is used to detect neurological disorders such as epilepsy, seizures, and sleep-related issues. Both ECG and EEG are non-invasive and play a crucial role in modern medical diagnostics.

Most existing systems focus on analyzing either ECG or EEG signals independently, which limits their ability to provide a comprehensive understanding of a patient's overall health. However, the heart and brain are closely interconnected through physiological and neurological pathways. Any abnormality in one system can influence the other, making it important to study both signals together for better diagnosis and monitoring.

To address this limitation, this project introduces NeuroCardio AI, a unified platform that integrates both of the Electrocardiogram (ECG) and Electroencephalogram (EEG) signal analysis using advanced AI techniques. The system is designed to accept multiple types of input, including raw signal data and images of medical reports, making it flexible and practical for real-world applications. By combining both domains, the system aims to provide a more holistic and accurate diagnostic solution.

The proposed system incorporates several stages such as data preprocessing, noise removal, normalization, feature extraction, and classification using deep learning models like Convolutional Neural Networks (CNN). The system processes ECG signals to detect heart-related abnormalities and EEG signals to identify brain-related conditions. The results are displayed through an interactive dashboard that provides clear and real-time insights to users.

Overall, this project not only focuses on accuracy and performance but also emphasizes usability and scalability. It can be applied in hospitals, telemedicine systems, and remote health monitoring environments, where quick and reliable diagnosis is crucial and this is also used to develop an efficient, scalable, and user-friendly healthcare system that enhances diagnostic capabilities by integrating cardiac and neurological analysis. NeuroCardio AI demonstrates the potential of artificial intelligence in advancing the multi-domain healthcare solutions, improving early detection of diseases, and contributing to better patient care and clinical outcomes.

2. LITERATURE REVIEW

Existing systems in biomedical signal analysis have made significant progress with the integration of Artificial Intelligence, particularly in analyzing physiological signals such as Electrocardiogram (ECG) and Electroencephalogram (EEG). These systems are widely used for detecting abnormalities in heart and brain activity, helping medical professionals in early diagnosis and monitoring. Machine learning and deep learning models, especially Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), have shown high accuracy in classifying patterns in these signals.

In the domain of Electroencephalogram analysis, many existing systems focus on detecting heart-related disorders such as arrhythmias, myocardial infarction, and other cardiovascular conditions. These systems use datasets like MIT-BIH Arrhythmia Database and apply preprocessing techniques such as filtering and normalization before feeding the data into AI models. The results are usually presented as classification outputs indicating normal or abnormal heart activity.

Similarly, EEG-based systems are designed to analyze brain signals for detecting neurological conditions such as epilepsy, seizures, sleep disorders, and cognitive states. These systems rely on feature extraction techniques and AI models to identify abnormal brain wave patterns. EEG analysis is widely used in clinical applications and research for understanding brain functionality and diagnosing neurological disorders.

Despite these advancements, most existing systems operate independently, focusing either on ECG or EEG signals. There is very limited integration between cardiac and neurological data analysis. This separation restricts the ability to study the interaction between both the heart and brain, even though both systems are interconnected through physiological processes.

Some research efforts have attempted to combine multiple physiological signals to improve diagnostic accuracy, but these implementations are often complex and not widely adopted in real-world applications. Additionally, many systems lack user-friendly interfaces and are not designed for real-time or scalable deployment, limiting their usability in practical healthcare environments.

Overall, existing systems provide strong performance in single-domain analysis but fall short in delivering a comprehensive, multi-domain diagnostic solution. This highlights the need for an integrated system that can analyze both ECG and EEG signals together, which is the primary motivation behind the development of the NeuroCardio AI project.

3. SYSTEM DESIGN

The system design of NeuroCardio AI follows a modular and layered approach to ensure flexibility, scalability, and efficient processing of both ECG and EEG signals. The system is divided into key components including data input, preprocessing, feature extraction, AI-based classification, and result visualization. Separate processing modules are designed for ECG and EEG signals to handle their unique characteristics, while a unified backend integrates both pipelines into a single workflow. The design supports multiple input formats such as raw signal data and medical report images, ensuring adaptability in real-world scenarios. Overall, the system is structured to provide accurate, real-time predictions through a seamless and user-friendly interface.

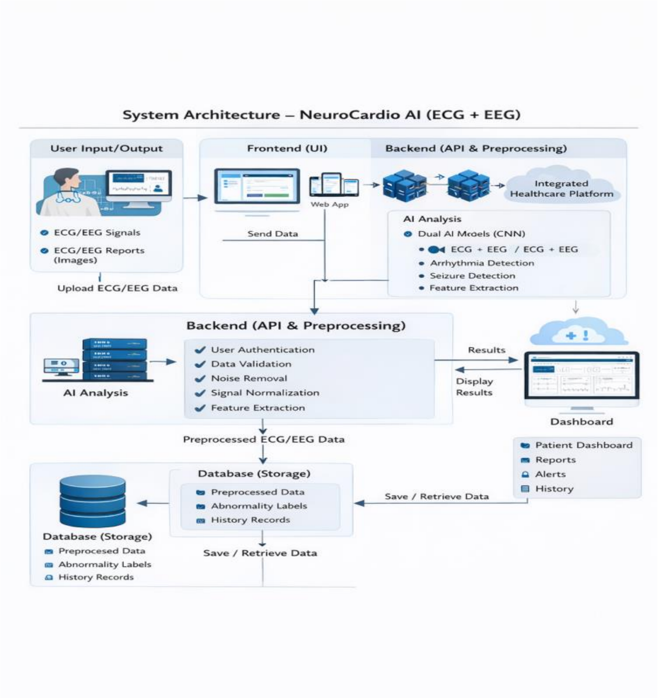

Figure 3.1- Model Architecture

The system architecture of NeuroCardio AI is designed as a layered structure consisting of a frontend interface, backend server, preprocessing module, AI analysis layer, and database. The user uploads ECG or EEG data through the frontend, which is then processed by the backend using techniques like noise removal and normalization. The processed data is passed to dedicated AI models for ECG and EEG classification, and the results are stored in the database and displayed on the dashboard. This unified architecture enables simultaneous analysis of heart and brain signals, making the system more efficient and comprehensive than traditional single-signal systems.

4. METHODOLOGY

1. Data Collection: The data used in this project is collected from publicly available biomedical datasets that contain labeled ECG and EEG signals. ECG data is primarily obtained from standard datasets such as the MIT-BIH Arrhythmia Database, which includes annotated recordings of different types of heartbeats. Similarly, EEG data is collected from clinical datasets that contain brain signal recordings associated with conditions like seizures and other neurological abnormalities. These datasets are widely used in research and provide reliable ground truth labels for training AI models.

In addition to raw signal data, the system is also designed to accept images of ECG and EEG reports. This enhances the flexibility of the application, allowing users to upload scanned reports or images captured from medical devices. The collected data is organized and stored in a structured format, ensuring that it can be efficiently used for preprocessing, training, and evaluation. Proper data handling is essential to maintain consistency and improve the overall performance of the system.

2. Image Preprocessing: When the input is provided in the form of images, image preprocessing techniques are applied to convert the visual data into usable signal information. The first step involves converting the image into grayscale to simplify processing and reduce computational complexity. This is followed by noise reduction techniques such as filtering to remove unwanted distortions present in the image. Resizing and normalization are also applied to standardize the image dimensions and intensity values.

After cleaning the image, the system extracts waveform patterns using techniques such as edge detection or contour extraction. These extracted signals are then converted into numerical arrays that resemble raw ECG or EEG signals. This step is crucial because it enables the system to process both digital signals and scanned reports in a unified manner. By doing so, the project increases its applicability in real-world scenarios where data may not always be available in structured formats.

3. Signal Preprocessing: Raw ECG and EEG signals often contain noise caused by external interference, muscle movements, or device limitations. Therefore, signal preprocessing is performed to enhance the quality of the data before feeding it into the model. Techniques such as bandpass filtering are used to remove unwanted frequency components, while normalization ensures that all signals have a consistent scale. This helps in improving the reliability of the extracted features.

In addition, denoising techniques such as wavelet transforms can be applied to further clean the signals. The processed signals are then segmented into smaller windows or frames to capture meaningful patterns. This step is important because it prepares the data in a format suitable for deep learning models. Proper preprocessing significantly improves the model's ability to learn and generalize from the data.

4. Feature Extraction: Feature extraction is a critical step in transforming raw signals into meaningful representations that can be used for classification. In this stage, important characteristics such as waveform peaks, frequency components, and temporal variations are identified. For ECG signals, features like P,Q,R,S complex, and T waves are crucial, while for EEG signals, different brain wave frequencies such as alpha, beta, theta, and delta are analyzed..

Advanced techniques such as time-domain and frequency-domain analysis are used to extract these features. In deep learning approaches, feature extraction can also be performed automatically by convolutional layers within the neural network. This reduces the need for manual feature engineering and allows the model to learn complex patterns directly from the data. Effective feature extraction plays a vital role in improving classification accuracy.

5.Model Building: The model building phase involves designing and training deep learning architectures to classify ECG and EEG signals. For ECG analysis, Convolutional Neural Networks (CNN) are commonly used due to their ability to capture spatial and temporal patterns in waveform data. The ECG model typically consists of multiple convolutional layers followed by pooling layers, which help in extracting hierarchical features from the signal. These features are then passed through fully connected layers to classify the signal into different arrhythmia categories such as Normal, Ventricular, or Supraventricular beats.

For EEG analysis, a similar deep learning approach is used, but with modifications to handle the complexity of brain signals. Models such as CNN or specialized architectures like EEGNet are employed to capture both temporal and frequency-based features of EEG data. In some cases, hybrid models like CNN-LSTM are used to capture both spatial and sequential dependencies in the signals. The EEG model classifies signals into categories such as normal, seizure, or abnormal brain activity. Both ECG and EEG models are trained using labeled datasets, optimized using techniques like learning rate scheduling and early stopping, and evaluated using metrics such as accuracy, precision, recall, and F1-score. The integration of these two models into a single system is the key innovation of this project, enabling simultaneous analysis of heart and brain signals.

6. Model Training & Testing: The model training and testing process was performed using a two-stage approach, consisting of initial training with frozen base layers followed by fine-tuning to improve performance. The Adam optimizer was utilized alongside the Categorical Cross-Entropy loss function for a duration of 50 epochs. Because the model training & testing required stability, this specific process was followed by the developers.

1. Accuracy: It describes the total rightness of the classification system when the calculation of the amount of right samples happens among the total group. It has been observed that accuracy provides a clear view of how well the system performs. The division of correct results by the total number of items is how accuracy is calculated because it represents the whole truth of the data.

2. Precision: Precision measures the proportion of correctly predicted positive cases. Precision is important because precision stops the wrong identification of healthy cases as sick cases. High results for precision are achieved when the predictions become more dependable. Reliable predictions are created by precision so that false positives stay at a low level.

3. Recall: The capacity of the model to find real tumor cases is measured by recall. Medical professionals state that this is necessary so that no tumors are missed during the checkup. Sensitivity is improved when recall numbers increase. Recall ensures that actual sickness is not ignored because recall focuses on finding every positive case.

4. F1-Score: A balanced assessment is provided by the F1 score which is the harmonic average of precision and recall. It has been observed that this becomes helpful when the reduction of both types of errors is required. Better performance of the whole system is shown by a high F1 score. F1-score remains a key value for researchers because F1-score combines two different measures into one.

5. RESULTS AND DISCUSSION

The results of the NeuroCardio AI system demonstrate its effectiveness in accurately classifying both ECG and EEG signals using deep learning models. The trained models are able to identify different categories of heart and brain conditions with high accuracy, based on the input data provided. For ECG signals, the system successfully detects arrhythmia patterns, while for EEG signals, it identifies abnormalities such as seizure activity. The performance of the models is evaluated using metrics such as accuracy, precision, recall, and F1-score, which indicate reliable and consistent results.

The system also provides real-time predictions through an interactive dashboard, making it easy for users to visualize and interpret the results. The inclusion of confidence scores helps in understanding the reliability of each prediction. By integrating both ECG and EEG analysis into a single platform, the system offers a more comprehensive diagnostic approach compared to traditional models. This dual-analysis capability enhances the overall usefulness of the system in clinical and remote healthcare applications.

From a discussion perspective, the results highlight the advantages of combining cardiac and neurological signal analysis. The system shows improved diagnostic capability by considering multiple physiological signals, which can help in identifying interconnected conditions. However, the performance of the model depends on the quality and diversity of the training data, and further improvements can be made by incorporating larger datasets and advanced architectures. Overall, the project demonstrates the potential of AI in developing efficient, scalable, and multi-domain healthcare solutions.

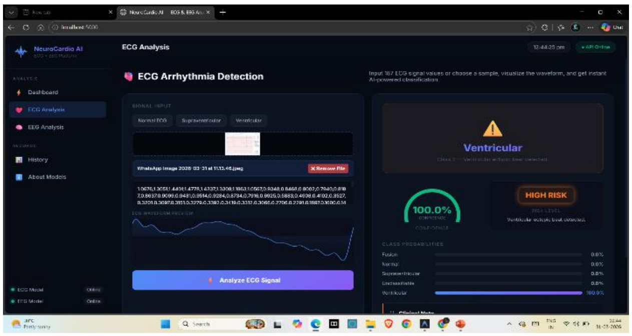

Fig 5.1: showing the heart disease in ventricles(ECG)

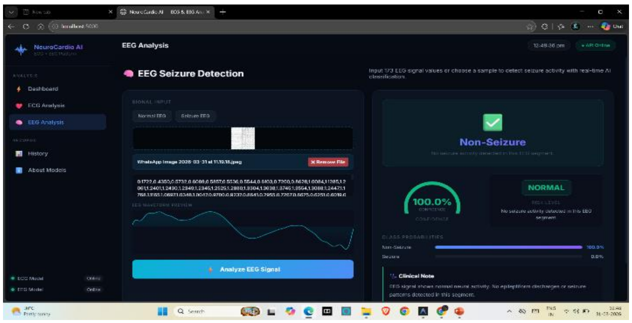

Fig 5.2: showing the output for EEG

6. CONCLUSIONS

In conclusion, this project successfully delivers a complete, end-to-end deep learning system for ECG arrhythmia classification that bridges the gap between research and real-world deployment. Through a robust data preprocessing pipeline, effective model architecture selection—particularly the high-performing Enhanced CNN—and advanced training strategies, the system achieves strong and reliable classification performance on standard benchmarks. While challenges remain in detecting rare classes such as Fusion beats, the results are consistent with existing research and validate the system's design. Moreover, the integration of a scalable Flask-based API and an interactive web interface demonstrates practical applicability in clinical settings. Overall, the project represents a meaningful advancement toward AI-assisted cardiac care, combining scientific rigor with deployment readiness and providing a strong foundation for future improvements and clinical integration.

7. REFERENCES

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