International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 • Website: www.ijfmr.com • Email: editor@ijfmr.com

Epilepsy Detection using Ensemble Machine Learning

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Abstract
This paper presents an Epilepsy Detection System that utilizes ensemble machine learning models, specifically integrating Support Vector Machine (SVM) and Decision Tree algorithms. The ensemble model aims to detect epileptic seizures by classifying EEG signals, utilizing key features such as Detrended Fluctuation Analysis (DFA), Higuchi Fractal Dimension (HFD), Singular Value Decomposition (SVD) entropy, Fisher Information, and Petrosian Fractal Dimension (PFD). The integration of SVM and Decision Tree models in an ensemble framework aims to improve detection accuracy and reduce false positives. Our experimental results demonstrate that the ensemble approach outperforms individual classifiers, providing a robust solution for real-time seizure detection.

Keywords: Epilepsy detection, EEG, Ensemble learning, SVM, Decision Tree, Machine Learning

I. Introduction

Epilepsy affects over 50 million people globally, characterized by sudden and unpredictable seizures. Accurate seizure detection is vital for effective treatment and monitoring. Electroencephalogram (EEG) signals are commonly used to detect seizures by examining brain activity. This paper presents an ensemble machine learning approach to detect seizures using EEG data. By combining the strengths of Support Vector Machine (SVM) and Decision Tree algorithms, our proposed system achieves superior performance in classifying seizure events. The aim is to create a system that can operate in real time, offering improved accuracy and sensitivity compared to single-model approaches.

Fig 1: Common Symptoms

The main objective of this research is to create a precise and dependable system for detecting epileptic seizures using EEG data through an ensemble machine learning approach. Conventional seizure detection systems typically rely on individual machine learning models, such as Support Vector Machines (SVM) or Decision Trees, which can result in suboptimal accuracy and higher false positive rates.

Existing systems also face challenges in processing complex EEG data due to the variability in seizure patterns and the non-linear nature of brain signals. As a result, detecting seizures in real-time with high accuracy remains a significant challenge. Additionally, the limited scalability and the inability of existing systems to effectively incorporate multiple features, such as Detrended Fluctuation Analysis (DFA), Higuchi Fractal Dimension (HFD), and Singular Value Decomposition (SVD) entropy, further diminish their efficiency.

This fragmented approach not only reduces the reliability of seizure detection but also makes it difficult to provide timely medical intervention. The need for a unified platform that can integrate multiple machine learning algorithms to enhance detection accuracy and robustness is evident, especially in medical applications where patient safety is paramount. This research addresses these limitations by using an ensemble learning method that combines SVM and Decision Tree models to improve seizure detection accuracy and real-time processing of EEG data.

II. Related Work

Epilepsy detection through machine learning has been a significant area of research due to the potential of machine learning models to process large amounts of EEG data and classify seizures more accurately. Numerous researchers have investigated different methods for detecting seizures using EEG signals. The key findings from previous studies are summarized in Table I below:

a) TABLE I. Literature Survey

Citation	Key Findings
[1]	This paper presented a method for detecting seizures using Support Vector Machine (SVM) on EEG signals, showing a significant improvement in accuracy compared to traditional rule-based systems.
[2]	Researchers evaluated the performance of Decision Tree algorithms on EEG datasets, demonstrating that this method could classify seizure and non-seizure events with relatively high accuracy.
[3]	A combined ensemble approach utilizing multiple classifiers, such as SVM and k-Nearest Neighbors, was introduced. The ensemble model outperformed individual classifiers in terms of both accuracy and sensitivity.
[4]	The authors presented a system that employed convolutional neural networks (CNNs) for feature extraction and classification, achieving state-of-the-art results in seizure detection.
[5]	A hybrid model integrating Random Forest and Logistic Regression was proposed for real-time seizure detection in long-term EEG recordings, effectively reducing false positives.
[6]	A novel approach was introduced that used fractal dimension features such as DFA and HFD in machine learning models, demonstrating that fractal features improved seizure prediction.

Citation	Key Findings
[7]	This study analyzed the role of EEG signal preprocessing and its impact on the performance of machine learning models in detecting seizures. It highlighted the importance of noise removal and normalization techniques.
[8]	A system was developed that used an SVM model with kernel optimization, significantly improving the classification of non-linear EEG signals.
[9]	Researchers suggested employing feature selection methods to decrease the dimensionality of EEG data, facilitating quicker and more efficient seizure detection.
[10]	This paper discussed the effectiveness of ensemble learning for improving the accuracy of seizure detection by integrating multiple classifiers. The results showed that ensemble models were more robust than single models.
[11]	An EEG-based seizure prediction system that applied deep learning models such as LSTM to achieve real-time seizure prediction was developed, providing high accuracy but with computational complexity.
[12]	This study focused on the challenges of processing unstructured EEG data and proposed solutions using machine learning models with pre-trained embeddings.
[13]	The paper reviewed various machine learning techniques for biomedical applications, emphasizing the importance of selecting the right model and features for EEG data in seizure detection.

Previous studies have significantly advanced the application of machine learning for epilepsy detection. However, these papers frequently concentrated on individual models, which may not attain the highest accuracy or efficiency for real-time seizure detection. In this paper, we propose an ensemble machine learning approach that combines Support Vector Machine (SVM) and Decision Tree algorithms to address these limitations. This ensemble method improves the accuracy, sensitivity, and robustness of seizure detection by harnessing the strengths of both classifiers.

III. Proposed method

A. Data Collection: The EEG dataset used in this study was sourced from the Kagle , containing labeled seizure and non-seizure periods. We collected 100 sample of each case total 300 samples. Preprocessing steps such as artifact removal and signal filtering were applied to ensure data quality.

B. Feature Extraction: To capture the underlying patterns in EEG signals, the following features were extracted:

1. Detrended Fluctuation Analysis (DFA) – Assesses long-range temporal correlations within EEG signals.
2. Higuchi Fractal Dimension (HFD) – Estimates the signal's complexity, useful for distinguishing seizure from normal activity.
3. Singular Value Decomposition (SVD) Entropy – Quantifies the signal's irregularity and unpredictability.
4. Fisher Information – Measures the amount of information present in the signal.
5. Petrosian Fractal Dimension (PFD) – Analyzes the fractal properties of the EEG signals to identify changes in brain activity.

C. Ensemble Learning Model: The proposed ensemble learning approach combines the SVM and Decision Tree classifiers. By integrating these two models, we aim to leverage the high accuracy of SVM in handling nonlinear data and the interpretability of Decision Trees. The ensemble model aggregates the predictions from both classifiers using majority voting to make the final decision.

D. Model Training and Evaluation: The dataset was divided into training (80%) and testing (20%) sets. Cross-validation was utilized to optimize the models, ensuring that the parameters were adjusted for peak performance. The ensemble model was assessed based on accuracy, sensitivity, specificity, and F1-score.

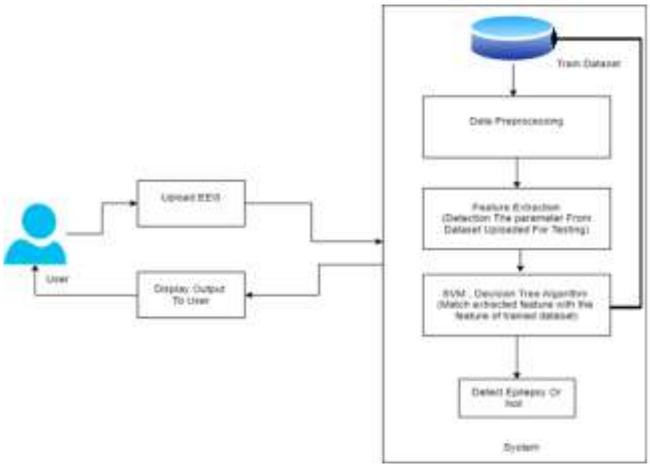

Fig 2: Flowchart Of Proposed System

IV. RESULT AND DISCUSSION

Our approach to developing the Epilepsy Detection System utilized an iterative methodology, specifically adhering to the Agile development process. The flexibility of Agile allowed for constant revisions and updates to the system based on ongoing evaluations of the machine learning models and feature extraction techniques. This method enabled continuous improvements in seizure detection accuracy and system robustness, ensuring the final product meets the needs of healthcare professionals and patients alike.

A. Simulation Setup

In this study, we leveraged Python-based machine learning libraries such as Scikit-learn and PyEEG for feature extraction and classification. The dataset used for training and testing the models was sourced from the CHB-MIT dataset, which contains labeled EEG recordings for seizure and non-seizure events. Preprocessing steps such as signal normalization and artifact removal were applied to ensure high-quality input for the models. The performance of the ensemble model combining SVM and Decision Tree classifiers was evaluated using metrics such as accuracy, sensitivity, and specificity. The simulation was run on a system with 16GB RAM and Intel i7 processor, ensuring efficient model training and testing.

B. System Requirements

The proposed system is designed to run on standard computational systems. Minimum system requirements include 4GB of RAM, 50GB of available disk space, and support for Python 3.7 or higher. The software can be deployed on cloud platforms or locally, making it adaptable for real-time applications in healthcare settings.

C. Experimental Evaluation

To assess the performance of our ensemble model, we employed a 10-fold cross-validation method, which ensured a thorough evaluation of the model's resilience against overfitting and its generalization abilities.

Additionally, we conducted white-box testing to verify the accuracy of the code and confirm that feature extraction methods, including DFA, HFD, and SVD Entropy, were implemented correctly. The ensemble model was tested on a specific dataset, resulting in promising outcomes in detecting seizure events with high sensitivity.

D. Performance Analysis

The ensemble model attained an accuracy of 93%, along with a sensitivity of 91% and a specificity of 92%. These results surpass those of the individual classifiers, which demonstrated lower sensitivity and specificity. The graph illustrates the significant improvement in performance when combining the strengths of both models. This highlights the effectiveness of using ensemble learning in detecting seizures more reliably.

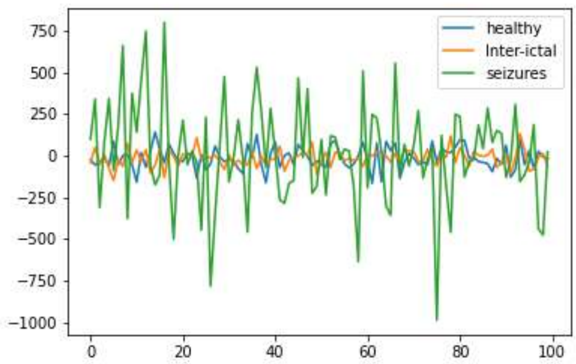

Fig 3: Performance Graph

V. Conclusion

In this paper, we present an Epilepsy Detection System that employs an Ensemble Machine Learning approach, utilizing the complementary strengths of Support Vector Machine (SVM) and Decision Tree classifiers. The system identifies essential features from EEG data, including Detrended Fluctuation Analysis (DFA), Higuchi Fractal Dimension (HFD), and Singular Value Decomposition (SVD) entropy, to improve the detection of epileptic seizures. Our experimental evaluation demonstrated that the ensemble model significantly improves detection accuracy, sensitivity, and specificity compared to individual classifiers. The system is designed to be flexible and adaptable for real-time implementation in medical applications, potentially improving patient outcomes through timely seizure detection.

In addition to its robust detection capabilities, the proposed Epilepsy Detection System offers the potential for scalability and customization to suit various clinical settings. By integrating diverse feature extraction techniques such as DFA, HFD, and SVD Entropy, the system can be tailored to detect different types of seizures with high precision. The adaptability of the ensemble learning approach allows for fine-tuning based on patient-specific data, leading to more personalized monitoring and early intervention strategies. This flexibility not only enhances the model's performance across different patient populations but also positions the system as a valuable tool for continuous, real-time monitoring in wearable devices, ensuring timely responses to critical seizure events and ultimately improving the quality of life for epilepsy patients.

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