A Robust Machine Learning Method for Real-Time Epileptic Seizure Detection in EEG

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Abstract. *The classification of EEG signals plays a critical role in the early detection of epileptic seizures, enabling timely intervention. Logistic Regression (LR) is a computationally efficient algorithm, making it particularly suitable for rapidly identifying seizure patterns within EEG data. This research introduces a machine learning (ML) method designed to categorize EEG patterns, distinguishing between normal and seizure-like signals. The proposed approach leverages a logistic regression-based seizure detection (LRSD) algorithm for accurate classification. In preprocessing, a finite impulse response (FIR) filter removes noise and artifacts from the EEG signals to improve signal quality. To boost the reliability of seizure detection, the algorithm utilizes seven distinct features, calculated to enhance statistical robustness. Additionally, multi-frequency characteristics are extracted using wavelet filters, enabling a comprehensive analysis in the frequency domain. This work benchmarks the proposed LRSD model against leading methods, with results showing that the new approach achieves a peak accuracy of 100% on the tested dataset.*

Keywords: - Logistic Regression EEG Classification, Machine Learning, Power Spectral Density.

Introduction

The use of electroencephalograms (EEG) for feature extraction has garnered significant attention due to its crucial role in the identification and prognosis of various brain illnesses. Diagnosing seizure disorders and determining the functionality of brain-related conditions is quite challenging. Over the years, multi-channel EEG experiments have become an active research topic for automatic seizure identification [1]. Consequently, numerous studies have recently been conducted to utilize traditional machine learning approaches to distinguish between different types of epileptic seizures using EEG samples. Machine learning (ML) classifications are highly effective in uncovering associated patterns, making them ideal for classifying EEG patterns and identifying seizures. Epilepsy is a neurological condition characterized by recurring seizures. Epileptic seizure detection (ESD) has become a critical area of clinical study and research, focused on effectively detecting the onset of a seizure. Early detection is vital for patient safety, prompt intervention, and improved seizure treatment.

Many key techniques from recent research can be applied to develop an effective Logistic Regression-based Machine Learning (LRML) strategy for EEG epileptic seizure identification. Discrete Wavelet Transform (DWT) is a promising framework used to extract features from EEG signals. This approach allows the model to better identify seizure patterns by capturing the time-frequency properties of the signals [2] [3]. High accuracy rates have been demonstrated when DWT is combined with statistical features, including Hjorth parameters; in certain studies, logistic regression has achieved up to 95.5% accuracy. Furthermore, the incorporation of entropy-based features has been highlighted as beneficial for classification tasks, suggesting that a multifaceted strategy combining both conventional ML and deep learning (DL) algorithms could enhance the robustness of the LRML model [4]. Overall, employing these advanced methods can result in a more reliable and efficient seizure detection system. Hybrid models that combine CNN and RNN classifiers have demonstrated that using genetic algorithms for optimal feature selection can further improve detection rates [5].

II Literature Review

Research on epileptic seizure detection (ESD) has evolved significantly, leveraging machine learning and deep learning to improve accuracy and reliability in various ESD models.

Tanishk Thakur et al. [1] introduced an Internet of Health Things (IoHT) system integrating multiple technologies for enhanced detection. They used pre-processing techniques to extract features, such as statistics, wavelets, and Hjorth parameters, followed by machine learning classification. By combining Discrete Wavelet Transform (DWT), Hjorth parameters, and statistical features, they achieved improved results, with a Support Vector Machine (SVM) classifier yielding a high accuracy rate of 93%. Similarly, M. Shamim Hossain et al. [2] utilized an EEG dataset from Boston Children's Hospital to train a convolutional neural network (CNN) model, achieving exceptional precision (98.05%) across 23 patients, with sensitivity and selectivity rates of 90% and 91.65%, respectively. This cross-patient ESD model has demonstrated superior performance over previous methods, showing effectiveness in recognizing epileptic patterns across various patients. Min Wu and Hong et al. [3] applied discrete wavelet transformation (DWT) combined with a long short-term memory-like spiking neuron model (LSTM-SNP) to capture time-frequency characteristics. Their method achieved 98.25% precision on the CHB-MIT dataset, proving effective for early seizure detection. Meanwhile, Noor Kamal et al. [4] distinguished seizure and non-seizure brain activity in children using EEG data from Ibn Rushd Medical Training Hospital. This study employed both machine learning (SVM, k-nearest neighbors, and decision trees) and deep learning classifiers (GRU, LSTM, and BiLSTM). Their findings indicated that RNN classifiers with GRU, LSTM, and BiLSTM, trained on entropy-based features, enhanced classification accuracy. R. Priyanka et al. [5] focused on performance evaluation by comparing machine and deep learning models. Using an Enhanced Fitness Function Genetic Algorithm (IGA) for feature selection alongside a CNN-RNN classifier on EEG data, they improved seizure detection rates, demonstrating the utility of feature optimization for accurate classification. Alshaya H. et al. [6] developed a deep learning model using ResNet and LSTM layers to prevent issues like gradient vanishing, achieving robustness by balancing data with the Synthetic Minority Oversampling Technique (SMOTE). This approach, tested on the TUH database, highlights the efficacy of data balancing and advanced architectures in ESD. Ulvi Başpınar et al. [7] employed Whole Harmonic Mode Segmentation for statistical feature extraction from EEG signals, confirming the robustness of their method in distinguishing seizures. Saminu S., Xu et al. [8] reviewed multiple ESD algorithms, including deep learning, and emphasized the importance of accurate detection methodologies. Their work serves as a foundation for future research in epileptiform identification and disorders of consciousness (DOCs). Other research has focused on optimization and computational efficiency. Ali Alqahtani et al. [9] applied hierarchical feature selection with an SVM classifier, achieving binary classification of seizure-related EEG data. Jeppesen J. et al. [10] introduced an adaptive algorithm based on LRML-classifier technology to improve patient-specific seizure identification. Further innovative techniques include Tran LV et al.'s [11] use of binary particle swarm optimization to reduce data dimensionality for faster seizure classification, achieving reduced processing times with significant accuracy. Subasi A. et al. [12] explored principal component analysis (PCA), independent component analysis (ICA), and linear discriminant analysis (LDA) for dimensionality reduction, enhancing seizure prediction with SVM classification.

Research continues to explore seizure prediction using neural networks, wavelet transformation, and genetic algorithms, balancing accuracy and computational efficiency. These efforts reflect a growing focus on wearable ESD devices for real-time monitoring, making advancements in seizure classification accessible and effective for patients and caregivers alike.

III Proposed Methodology

This study proposes the use of a wavelet-based classifier for frequency feature extraction and extended statistical features for ESD and classification. The primary objective of the research is to evaluate the performance of a logistic regression (LR) based machine learning approach for ESD and seizure classification. The proposed system diagram of the methodology is illustrated in Figure 1. Initially, the data of EEG patterns are acquired in the MATLAB environment. The CHB-MIT dataset is used, with two classes defined as a binary classification problem in this research: the normal class with seizure-free EEG (N) and the second class containing seizure EEG patterns (S). A total of 25 EEG signals from each class are considered for the experiment.

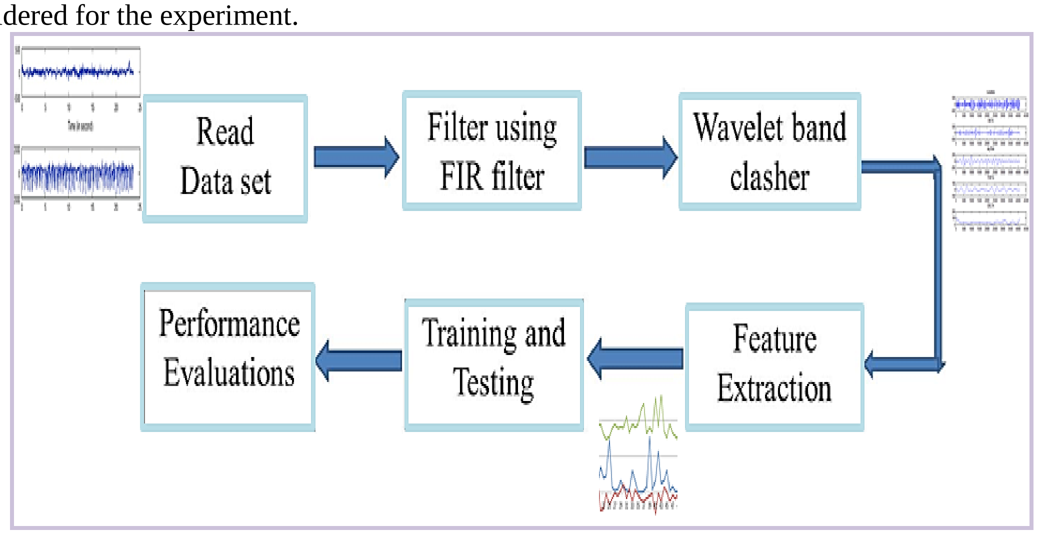
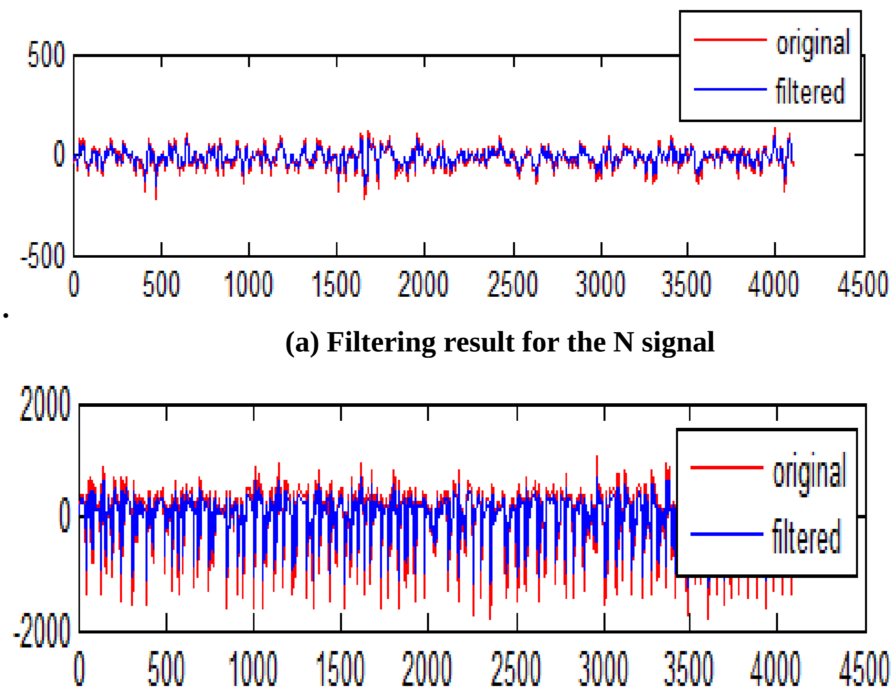


Figure 1: Proposed EEG Classification System.

At the front end, any external noise is eliminated using an FIR filter, which is simple, efficient, and does not alter the true nature of the EEG data. Then, multi-band frequency features are extracted using wavelet-based classifiers. Extended statistical features, with seven features of the EEG patterns, are calculated. Finally, the feature vectors are used for the evaluation of different classifiers' performance using the proposed dataset. The feature vector data is sorted before being used.

IV Experimental Results & Discussion

In this section, we present the anticipated results of preprocessing and classification for the proposed Logistic Regression-Machine Learning (LR-ML) based methodology, including a performance comparison with leading-edge classifiers. Initially, the filtering results achieved through the FIR filter are demonstrated in Figure 2. These results indicate that the essential characteristics and overall structure of the EEG signal are effectively maintained after filtering, ensuring minimal information loss while removing noise and artifacts. This preservation of the signal's natural profile is crucial for accurate feature extraction and reliable classification.

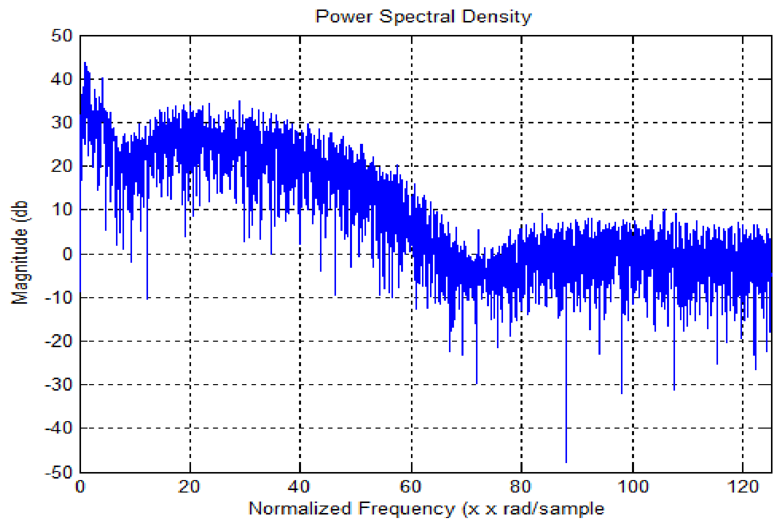


(a) Filtering result for the N signal

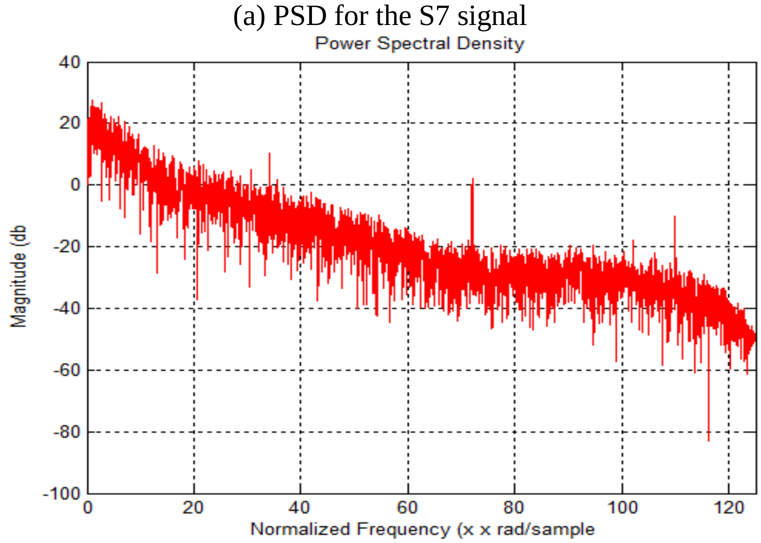
(b) Filtering result for S signal

Figure 2: Results of EEG signal with FIR Filtering.

Additionally, Figure 3 illustrates the Power Spectral Density (PSD) calculated for both seizure (S) and non-seizure (N) classes using a representative signal sample from the dataset. The PSD analysis reveals a notable increase in power for the seizure signals compared to non-seizure signals, which serves as a distinctive feature for seizure classification. This contrast in PSD levels between S and N classes highlights the discriminative power of frequency-domain features in distinguishing seizure activity.



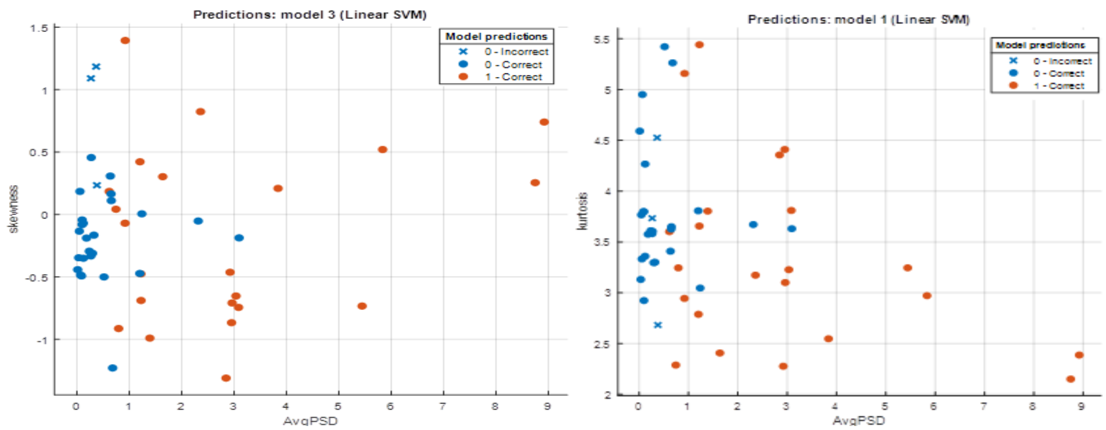
(a) PSD for the S7 signal



(b) PSD for the N7 signal

Figure 3: Results comparison of calculated Power Spectral Density (PSD) for N and S classes of EEG.

Furthermore, the classification accuracy is visually represented in the scatter plots shown in the second row of Figure 4. These plots make the accuracy ratio apparent, providing a clear, visual confirmation of the classification performance. Through these analyses, the LR-ML model's effectiveness in EEG-based seizure detection is reinforced, demonstrating its capability to outperform state-of-the-art methods in both accuracy and computational efficiency. The results underscore the model's potential as a reliable and high-performance tool for clinical seizure diagnosis.



(a) For SVM (b) For LR

Figure 4: Scatter plots.

V Conclusions and Future Scope

In conclusion, this study introduces a robust and computationally efficient machine learning approach based on logistic regression for the classification of EEG patterns, specifically aimed at detecting epileptic seizures. The research addresses a significant need for rapid and accurate seizure detection by combining several methodological strengths: the use of an FIR filter to effectively minimize noise and artifacts, the extraction of enhanced statistical features to improve classifier performance, and wavelet-based multi-frequency analysis for thorough frequency domain examination. Together, these techniques enable the proposed LR-based seizure detection model to achieve exceptionally high classification accuracy. When tested and compared with other state-of-the-art methods, the proposed model outperforms alternatives, reaching a maximum accuracy of 100% on the dataset considered. This impressive level of accuracy underscores the model's potential as a powerful tool for real-time seizure detection, with critical implications for improving patient outcomes through earlier and more reliable diagnosis of epilepsy. Furthermore, the approach opens pathways for further exploration in EEG-based diagnostic applications, with potential for adaptation to other neurological disorders. Overall, the study provides valuable insights and contributions to the field of medical signal processing, laying the groundwork for more advanced, efficient, and accessible seizure detection systems.

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