MLP-Driven Epilepsy Diagnosis: A Novel Approach Using EEG Features and Signal Analysis

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ABSTRACT

Epilepsy is one of the most widespread neurological disorders, with nearly one in ten individuals expected to experience a seizure at some point in life, and a significant portion of these cases developing into epilepsy. This work presents a Clinical Decision Support System (CDSS) designed to assist in the diagnosis of epilepsy using a Multilayer Perceptron (MLP) neural network. The system analyzes electroencephalogram (EEG) signals to differentiate between normal and interictal brain activity. Feature extraction is carried out using Principal Component Analysis (PCA) and Discrete Wavelet Transform (DWT) to enhance classification performance. The study focuses on evaluating the MLP model's effectiveness in accurately identifying epileptic patterns, demonstrating its potential as a reliable tool for clinical diagnosis.

Keywords: ***Epilepsy Diagnosis, Electroencephalogram (EEG) Multilayer Perceptron (MLP), Principal Component Analysis (PCA), Neural Network (NN), Discrete Wavelet Transform (DWT)***

1. INTRODUCTION

Epilepsy is a prevalent neurological disorder characterized by abnormal electrical activity in the brain, often resulting in recurrent seizures. It is estimated that approximately 10% of individuals will experience at least one seizure in their lifetime, and nearly one-third of them may develop chronic epilepsy. These seizures can lead to various symptoms, including unusual sensations, emotional disturbances, involuntary movements, and, in some cases, a temporary loss of consciousness. The causes of epilepsy are diverse and may include brain injuries, infections, genetic factors, or developmental abnormalities affecting normal brain function.

Electroencephalography (EEG) is a primary diagnostic tool for epilepsy, offering a non-invasive way to monitor and record brain wave patterns. EEGs are particularly valuable as they can detect irregularities in brain activity even when a person is not actively experiencing a seizure. Despite its diagnostic utility, access to EEG analysis and appropriate treatment remains limited in many regions. According to a 2009 World Health Organization (WHO) report, nearly 50 million people globally live with epilepsy, with 90% residing in low- and middle-income countries. Unfortunately, about 75% of these individuals do not receive the necessary treatment due to socioeconomic barriers and widespread social stigma, particularly in countries such as India and China, where epilepsy may be seen as a social impediment.

To overcome the limitations of manual interpretation of EEG signals and enhance diagnostic accuracy and accessibility, researchers have increasingly focused on developing computer-aided diagnostic systems. Early efforts utilized conventional computational approaches such as fuzzy logic and genetic algorithms for seizure detection. One of the pioneering efforts in this domain was Gotman's work in 1982, which laid the groundwork for automated EEG-based seizure detection systems. Over time, the research community has shifted toward machine learning-based techniques, especially artificial neural networks, due to their ability to model complex, nonlinear patterns in EEG signals. EEG's non-invasive nature and high sensitivity to neurological abnormalities make it a prime candidate for automated seizure analysis. Foundational studies by Gotman [10] and Andrzejak et al. [12] demonstrated that neural networks could effectively be used to analyze EEG data and identify deterministic patterns associated with seizures.

The wavelet transform has gained traction as a powerful signal processing technique, offering time-frequency localization crucial for detecting transient events in EEG. Harikumar and Narayanan [4] applied fuzzy techniques to classify epilepsy risks, while Harikumar et al. [5] used genetic algorithms, both illustrating the usefulness of

heuristic methods in the classification of epileptic EEG data. Szilagyi et al. [6] demonstrated that combining wavelet decomposition with neural networks could enhance the reliability of epilepsy detection systems.
Building on these foundations, researchers like Srinivasan et al. [7][13] incorporated approximate entropy with neural networks, enabling more refined detection of irregularities in EEG signals. Kumar et al. [14] extended this approach by integrating wavelet entropy features with recurrent neural networks, showcasing the
These developments underscore the potential of AI-driven systems to enhance the speed, accuracy, and accessibility of epilepsy diagnosis. This research aims to build upon these advancements by leveraging artificial intelligence—particularly the Multilayer Perceptron (MLP) neural network—for accurate classification of epileptic EEG signals, using advanced feature extraction techniques for improved performance and clinical relevance.
This paper investigates the use of a Multilayer Perceptron (MLP) neural network for the diagnosis of epilepsy through EEG signal analysis. The problem of epilepsy diagnosis is framed as a two-class classification task, distinguishing between 1) healthy subjects (normal EEG) and 2) epileptic subjects during the seizure-free interval (interictal EEG). MLP is employed as the core model for the decision support system, with two feature extraction methods—Principal Component Analysis (PCA) and Discrete Wavelet Transform (DWT)—used to enhance the network's classification accuracy. The MLP-based system aims to streamline the diagnostic process, offering a cost-effective and time-efficient solution for clinicians. By automating the detection of epileptic patterns, the system allows doctors to focus on treating actual patients, improving the overall efficiency of healthcare delivery.

2. EE DATA BASE

The EEG data used in this study were collected from the Department of Psychiatry at J. N. Medical College, Swangi Meghe, Wardha, Maharashtra, India. To create the datasets, recordings were made from six healthy individuals and six patients with abnormal EEG patterns. The EEG signals were recorded according to the international 10-20 electrode placement system. Two distinct datasets were formed from these recordings: dataset 'a' and dataset 'd'. Dataset 'a' consists of 70 single-channel EEG segments from healthy individuals, while dataset 'd' includes recordings from epileptogenic zones during seizure-free intervals in epileptic patients.

The EEG signals were captured using a 24-channel amplifier system, with an average common reference, and sampled at a rate of 173.61 Hz following a 12-bit analog-to-digital conversion. A band-pass filter with settings of 3–15 Hz was applied. The data were recorded continuously and stored on a data acquisition computer. Further processing and experimentation with these EEG signals were conducted at the Research Laboratory of the Department of Applied Electronics at Sant Gadge Baba Amravati University, Amravati. This dataset is referred to as the "JNM dataset."

3. SELECTION OF NEURAL NETWORK PARAMETERS

The neural networks were developed through systematic optimization of parameters to ensure effective classifier performance. The training parameters were chosen based on their ability to deliver the best classification accuracy. Performance was evaluated by the average classification accuracy obtained during various experiments. Through repeated testing, optimal values were determined for key parameters, including the number of hidden layers, the size of each hidden layer, the momentum constant, learning rate, and the type of activation functions. The data for training, testing, and cross-validation were selected using a trial-and-error approach in each experiment.

4. DESIGNED OF PCA BASED NNs

To handle the high dimensionality of the input features in the EEG dataset, Principal Component Analysis (PCA) was employed for dimensionality reduction. Among various transformation rules considered, the Spearman correlation method was selected due to its superior performance in capturing meaningful variance from the data. Spearman-based PCA ranks the variables and computes correlations based on these ranks, making it more robust to non-linear relationships and outliers—common in EEG signals. Using XLSTAT 2011, PCA with the Spearman method was applied, and the number of principal components (PCs) was gradually increased to identify the optimal input feature space. Network performance was evaluated using metrics such as cross-validation Mean Squared Error (MSE), testing MSE, and classification accuracy. It was observed that when 20 principal components were used, the MLP neural network achieved its best performance, with the lowest error rates and highest classification accuracy. This confirms the effectiveness of the Spearman approach in enhancing the quality of features for EEG-based epilepsy classification. The performance metrics of the Multilayer Perceptron (MLP) model are presented in Table 1. Additionally, the Receiver Operating Characteristic (ROC) curve for the testing dataset is illustrated in Fig. 2.

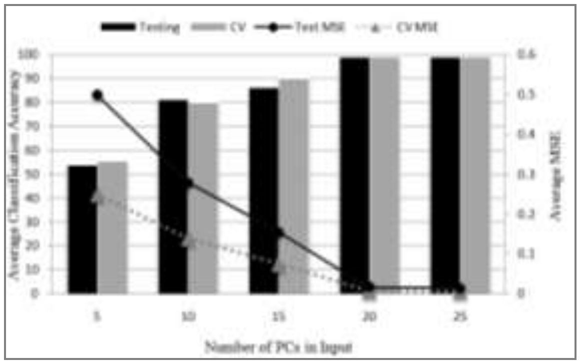

Figure 1. Variations in MSE and classification accuracy with a number of PCs as inputs.

5. DISCRETE WAVELET TRANSFORM

A signal transform provides an alternative representation of the original signal without altering its inherent information. The Wavelet Transform is particularly useful because it captures both time and frequency characteristics of the signal. The Continuous Wavelet Transform (CWT), defined in Equation (1), analyzes a signal *x(t)* by correlating it with scaled and shifted versions of a core waveform known as the mother wavelet *ψ(t)* All basis functions used in the transformation are generated by modifying the mother wavelet through scaling (compressing or stretching) and translation (shifting in time):

$$X_{WT}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t).\psi\left(\frac{t-\tau}{s}\right) dt \qquad (1)$$

In this equation, the translation parameter τ determines the position of the wavelet along the time axis, capturing time-based features of the signal. The scale parameter sss, inversely related to frequency, adjusts the wavelet's resolution larger scales (low frequencies) highlight fine details, while smaller scales (high frequencies) emphasize overall trends.

While the CWT provides detailed analysis, it is computationally demanding. To address this, the Discrete Wavelet Transform (DWT) offers a more efficient alternative by using sampled wavelet coefficients. DWT relies on the Mallat algorithm, which iteratively applies low-pass (G_0) and high-pass (H_0) filters to the input signal x[n]. The low-pass filter extracts approximation coefficients a[n], capturing coarse structure, while the high-pass filter yields detail coefficients d[n], highlighting high-frequency components. This multilevel filtering strategy efficiently decomposes the signal into different resolution levels with reduced computational cost.

6. SELECTION OF MOTHER WAVELET AND NUBER OF LEVELS

In Wavelet Transform analysis, the choice of the mother wavelet plays a critical role, as it determines the basis functions used throughout the transformation process via scaling and translation. Since the characteristics of the wavelet transform are directly influenced by this choice, it is essential to select a mother wavelet that aligns well with the specific nature of the application and the properties of the signal under study.

To identify the most suitable wavelet, several types were evaluated in terms of their ability to capture relevant features from EEG signals. Among the tested wavelets, the Daubechies wavelet of order 2 (DB2) demonstrated the best performance in detecting frequency changes within the EEG data. Consequently, DB2 was selected for the decomposition process.

The number of decomposition levels was determined based on the dominant frequency components present in the EEG signals. This approach ensures that the wavelet coefficients preserve the signal features most relevant for classification. The DB2 wavelet was applied to EEG recordings from both normal individuals and patients in interictal states, effectively extracting meaningful frequency-domain information for further analysis and classification.

7. FEATURE EXTRACTION

The wavelet coefficients extracted from EEG signals provide a detailed time-frequency representation, from which various statistical features are derived to form a consistent feature vector length. For this study, the following statistical parameters were calculated from the approximation and detail coefficients of a three-level wavelet decomposition:

1. Mean of the absolute values of the coefficients
2. Median of the coefficients
3. Maximum and minimum values in each sub-band
4. Range (difference between maximum and minimum values)
5. Standard deviation in each sub-band
6. Mean absolute deviation and median absolute deviation

These computations were applied to both approximation and detail coefficients across three decomposition levels, yielding a total of 48 statistical features. Additionally, five wavelet entropy measures Shannon, log energy, threshold, user-defined, and norm entropy were extracted. The percentage energy distribution across sub-bands was also calculated, contributing four more features. Altogether, the final input feature vector consisted of 57 attributes.

The Multilayer Perceptron (MLP) neural network was trained using these features. To ensure robust learning and generalization, the MLP was retrained three times with different random initializations of weights and biases. Various experimental configurations were tested, including adjustments to the proportion of training, testing, and validation data, as well as variations in hidden layer architecture, the number of processing elements, activation functions, and learning algorithms. The optimal MLP configuration was selected based on the highest classification accuracy and lowest mean squared error (MSE). The performance metrics of the Multilayer Perceptron (MLP) model are presented in Table 1. Additionally, the Receiver Operating Characteristic (ROC) curve for the testing dataset is illustrated in Fig. 3.

Table1: Performance parameter of MLP with 20 principal components input and Wavelet Transform as input

Input	Average MSE			%Average Classification Accuracy				Overall % Accuracy	% Sensitivity (Interictal)	% Specificity	Ʈ (in ms)
	Training	Testing	CV	Training	Testing	CV	Average				
PCA	$1.6*10^{-8}$	$6.3*10^{-8}$	$3.0*10^{-8}$	100	100	100	100	100	100	100	0.00051
DWT	0.003	0.009	0.008	99.97	99.23	99.22	99.47	99.21	98.46	100	7.37

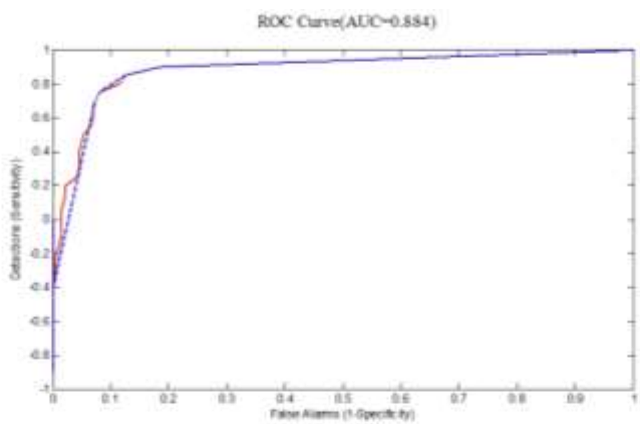

Fig.2: ROC during testing period for MLP with PCA as an input

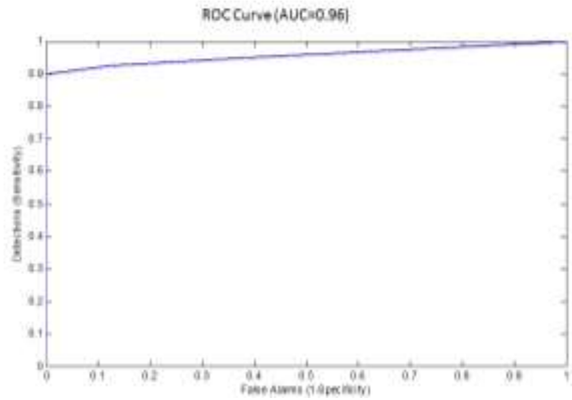

Fig.3: ROC during testing period for MLP for DWT as an input

8. CONCLUSION

In this research, a classification framework for epileptic EEG signals was developed using a Multilayer Perceptron (MLP) neural network, employing feature extraction techniques based on Principal Component Analysis (PCA) and Discrete Wavelet Transform (DWT). The classification task was modeled as a two-class problem, distinguishing between EEG recordings from healthy individuals and those from epileptic patients during seizure-free intervals (interictal EEG).

The MLP network was retrained multiple times with different random weight initializations to ensure reliable learning and consistent generalization. Its performance was evaluated based on average classification accuracy and the area under the Receiver Operating Characteristic (ROC) curve. When PCA-based features were used, MLP achieved an average classification accuracy among the highest across all tested models, with an ROC area of 0.884.

Further improvement was observed when features extracted using the DWT with Daubechies wavelet (DB2) were used as input to the MLP. In this configuration, the MLP demonstrated superior performance compared to other classifiers, achieving higher classification accuracy and a better ROC area. Additionally, the MLP proved to be computationally efficient, requiring only 0.51 microseconds per epoch per exemplar, making it a practical choice for real-time clinical applications.

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List of Abbreviations:

CV Cross Validation

DSS Decision Support System

EEG Electroencephalogram

NN Neural Network

N Number of exemplars in a data set.

PE Number of output processing elements (PEs).

PCA Principal Component Analysis

PCs Principal Components

PSD Power Spectral Density