Automated Depression Detection via EEG Signal Processing and Machine Learning

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Abstract— **Depression is increasingly recognized as one of the most widespread mental health disorders affecting individuals today. This paper proposes a reasoning-based model for the detection of depression using Electroencephalography (EEG) signals. EEG data were collected using a portable three-electrode device, pre-processed to eliminate artifacts, and subjected to feature extraction. The processed signals were then analysed using a Linear Pattern Recognition Network (LPRN), a type of machine learning algorithm. Wavelet transform was applied to the EEG signals to capture key frequency components relevant to depressive patterns. Frequency-specific features served as statistical indicators for further analysis. The system performs wavelet transformation on all collected EEG data and utilizes the output of the LPRN to generate statistical scores for classification. System performance was evaluated in terms of accuracy, using a confusion matrix that compares classified output with the training data. Furthermore, based on emotion classification derived from EEG patterns, the system also provides personalized music recommendations corresponding to the detected emotional state.**

Keywords— **Depression detection, EEG signal analysis, Emotion recognition, Machine learning, Wavelet transform, Linear pattern recognition.**

I. INTRODUCTION

The brain-computer interface (BCI) represents a novel communication pathway between the human brain and digital systems. Its primary objective is to aid individuals with physical disabilities by enabling movement restoration, communication, and control of external environments. An EEG-based BCI system has been integrated with a virtual reality (VR) environment to facilitate smart home control, acting as an alternative to natural communication and motor functions. This system serves as an artificial mechanism that bypasses traditional neuromuscular pathways [1]. Different cognitive states correspond to unique neural interaction patterns, which produce brain waves varying in amplitude and frequency. These interactions are driven by neuronal activity, where each neuron emits tiny electrical discharges. The proposed method captures these brain signals using EEG sensors, segments the data into packets, and transmits it via a wireless medium [2]. A wave measurement unit collects raw EEG data and converts it into usable signals through processing in the MATLAB GUI environment.

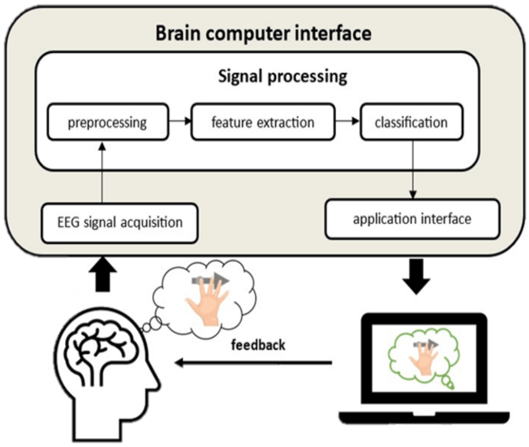

Fig 1. Brain Computer interfacing system

Fig. 1 depicts the brain-computer interfacing system. Accurately measuring brain-generated oscillations is fundamental to any BCI system, as these signals represent the voluntary neural activities associated with the user's current state. Numerous signal acquisition techniques have been investigated, and the choice of technique depends largely on the intended application and user profile of the BCI. Selecting the appropriate method is crucial for effectively capturing the relevant neural signals and ensuring optimal system performance [3].

Invasive recording methods involve implanting electrodes beneath the scalp to measure neural activity either intracortically within the motor cortex or on the cortical surface, known as electrocorticography (ECoG). These techniques offer high temporal and spatial resolution, resulting in superior signal quality and signal-to-noise ratio. However, they present several challenges. Aside from the invasiveness and associated surgical risks, the limited coverage area of the implanted electrodes restricts the brain regions that can be monitored. Once implanted, electrodes cannot be repositioned to capture activity from other areas [4]. Additionally, the body's immune response to the implant can cause complications, including implant instability and infection risks. Due to these limitations, invasive methods are typically reserved for medical BCI applications involving a small number of disabled users [5]. Most invasive BCI research has been conducted on animal models like monkeys, though some tetraplegic patients have benefited from implanted electrodes. The following subsection provides further details on these invasive techniques. Developing communication interfaces based on brain signals presents several challenges, which can be broadly classified into technical and usability challenges. Technical challenges primarily involve difficulties associated with the characteristics and processing of EEG signal features, as well as system constraints. Usability challenges pertain to factors that influence user acceptance and the overall practicality of the interface in real-world applications [6].

EEG signal variability reflects changes in mental and emotional states across sessions, influenced by factors such as fatigue and concentration, which contribute to internal non stationarities. Noise further complicates BCI systems, originating from electrode displacement and environmental interference. Additionally, artifacts from muscle activity (electromyogram, EMG) and eye movements or blinks (electrooculogram, EOG) are often present in the recorded signals, making it challenging to accurately identify neural patterns.

Another major challenge is the "curse of dimensionality." To achieve high spatial resolution, BCI systems record signals from multiple channels, resulting in high-dimensional data. As dimensionality increases, so does the complexity and the volume of data needed to represent the signals accurately. Feature extraction techniques are therefore essential to isolate the most relevant characteristics, enabling classifiers to focus on meaningful features and improve performance by reducing redundancy.

- The proposed model is developed using a linear pattern recognition algorithm applied to EEG data from the AMIGOS dataset.
- The EEG data undergoes preprocessing and cleaning to remove noise and artifacts, followed by feature extraction using the discrete wavelet transform (DWT).
- The dataset is partitioned into training (80%) and testing (20%) subsets, with the linear pattern recognition algorithm trained on the training data.
- Once trained, the model processes the testing data to extract features from the alpha, beta, gamma, theta, and delta frequency bands.
- The system's performance is assessed using evaluation metrics including accuracy, precision, and recall.

II. BACKGROUND STUDY

Ofner et al. (2017) examined the encoding of upper limb movements within the time domain of low-frequency electroencephalography (EEG) signals. The study involved fifteen healthy participants who performed six distinct sustained upper limb movements. The researchers classified these six movements along with a rest state, achieving average classification accuracies of 55% for differentiating between movements and 87% for distinguishing movement from rest during executed actions. For imagined (or expected) movements, the classification accuracies were 27% for movement differentiation and 73% for movement versus rest.

Suwannarat et al. (2018) employed eight-fold cross-validation on EEG data to assess classification accuracy. Both Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) classifiers demonstrated comparable performance. Features extracted from specific frequency bands (FB) yielded significantly higher classification accuracy compared to those derived from the whole-band (WB) approach. Across all subjects, classification of wrist flexion/extension movements achieved higher accuracy than hand opening/closing tasks. Forearm pronation/supination classification generally outperformed hand opening/closing but showed lower accuracy than wrist flexion/extension in all participants. Furthermore, analysis of single-session data from all motor imagery (MI) tasks revealed improved classification accuracy in nine patients.

J. Cheng et al. (2021) introduced a method that significantly reduces the dependence on feature extraction common in traditional approaches and employs a classification model that is insensitive to hyperparameter settings, thereby addressing major challenges in emotion recognition. The effectiveness of the proposed model was validated through experiments on two publicly available datasets, DEAP and DREAMER. On the DEAP dataset, the model achieved average accuracies of 97.69% for valence and 97.53% for arousal. On the DREAMER dataset, it attained average accuracies of 89.03% for valence, 90.41% for arousal, and 89.89% for dominance.

S. Liu et al. (2022) introduced a novel deep learning model named the three-dimensional convolutional attention neural network (3DCANN) for EEG-based emotion recognition. The 3DCANN architecture comprises a spatio-temporal feature extraction module alongside an EEG channel attention weight learning module. This design effectively captures both the dynamic temporal relationships and the internal spatial dependencies among multi-channel EEG signals throughout continuous time intervals.

Y. Gao et al. (2022) proposed a multi-view EEG-based emotion recognition method that effectively integrates distinctive features from EEG signals. The approach was extensively evaluated on two benchmark datasets, SEED and DEAP, demonstrating superior performance compared to other representative single-view and multi-view methods. The EEG-GCN model captures both critical sequential segments and spatial location information within EEG signals, enhancing its recognition capabilities.

III. SYSTEM DESIGN

One of the primary challenges in EEG-based emotion analysis is differentiating between passive and active emotion elicitation methods. Additionally, there remains a significant need for more efficient and user-friendly techniques for collecting emotional data. To address these issues, this study introduces a robust deep learning framework developed in MATLAB. The core objective is to design a lightweight algorithm that can accurately recognize emotional states and enable real-time decision-making within a minimal time frame.

The proposed approach leverages advanced signal processing techniques to preprocess raw EEG data, removing artifacts and enhancing signal quality. A carefully structured deep neural network is then trained on these signals to classify emotional states across multiple dimensions, such as valence and arousal. The model is optimized for performance on low-resource platforms, making it suitable for real-world applications such as wearable EEG devices or mobile health monitoring systems. Evaluation of the model is carried out using benchmark EEG datasets, and performance is measured in terms of accuracy, latency, and computational efficiency. The results demonstrate that the proposed method not only achieves high classification accuracy but also significantly reduces response time, thereby facilitating timely emotional assessments. This research contributes to the growing field of affective computing and opens up possibilities for its integration into adaptive human-computer interaction systems and personalized mental health care solutions.

METHODOLOGY

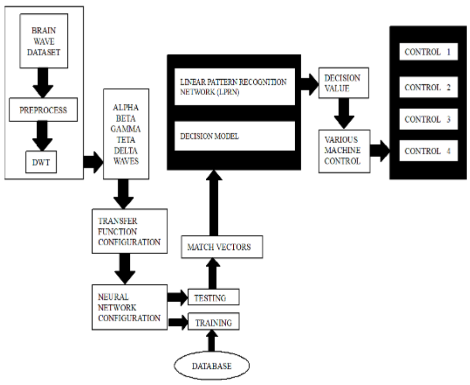

Fig 2. System architecture of LPRN brain wave analysis

Figure 2 presents the architectural framework of the proposed model for brainwave analysis.

B. Brainwave Data

Electroencephalography (EEG) captures the brain's real-time electrical responses to external stimuli during cognitive or physical tasks. EEG signals consist of various brainwave types, including Delta, Theta, Alpha, Sigma, and Beta waves, each characterized by specific frequency ranges:

- Delta: 0.5–4 Hz

- Theta: 4–7 Hz
- Alpha: 8–12 Hz
- Sigma: 12–16 Hz
- Beta: 13–30 Hz

These brainwaves represent low-amplitude electrical signals generated by neural activity and are recorded using multiple scalp-mounted electrodes—typically up to 256 channels, though 64-channel systems are commonly used. While EEG offers valuable insights into brain function, it is sensitive to noise and artifacts, particularly those caused by motion, which can interfere with signal accuracy and interpretation.

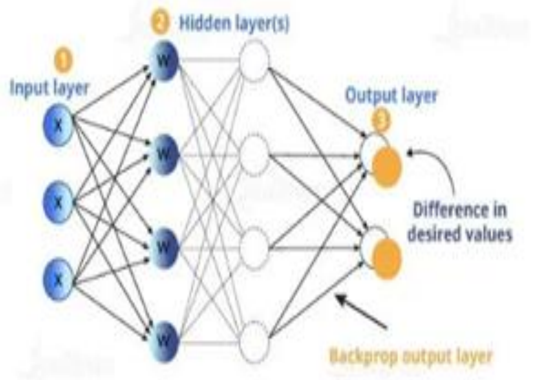

Figure 3: Neural structure of the proposed LPRN-Resi Net architecture.

Figure 3: Depicts the neural architecture of the proposed Novel Resi Net model, which integrates a back-fetching mechanism wherein residual weights are reused as bias updates to the input layers. The network utilizes the Sigmoid activation function—also known as a squashing function—due to its property of mapping input values to a finite output range, thereby stabilizing the learning process.

In the Resi Net framework, derivative values with excessively large magnitudes are disregarded, as they can disrupt the stability of weight updates. This is controlled by the back-fetching process, which effectively regulates gradient behaviour and mitigates the risk of overfitting.

he behavior of ResiNet is formally expressed in Equation (1):

$$y_1 = f_1\left(w_{(x1)}X1 + w_{(x1)}X2\right), \qquad (1)$$

Here, f_1 represents the functional derivative of the input x with respect to neuron X_1.

The final derivative used in backpropagation is derived in Equation (2):

$$Wn = \mu\delta \frac{dfn(e)}{de} yn \qquad (2)$$

This equation models the network across n layers, with a coefficient α that influences the training convergence rate. During training, parameter values are adaptively reduced, leading to optimal weight coefficients that closely align with the underlying data distribution.

Implementation Summary

The processed data from the AMIGOS dataset is divided into three main variables after completing data cleaning. EEG signals are then formally extracted for analysis. To characterize the EEG patterns, Discrete Wavelet Transform (DWT) is applied to estimate key parameters such as Sigma and Lambda. During this process, computational metrics including Algorithm Computation Time (ACT) and Full System Model Computation Time (FCT) are recorded.

The implementation follows these key steps:

- Feature Extraction and Model Setup: The LPRN model performs statistical analysis and extracts feature patterns, which are subsequently fed into the Resi Net neural network. The configured neural blocks are detailed in Figure 5.
- Correlation Analysis:
  Correlation parameters based on training and testing data from LPRN are computed and plotted to identify important data relationships.
- Performance Evaluation:
  System performance is assessed using a confusion matrix that quantifies True Positives, True Negatives, False Positives, and False Negatives.
- ROC Curve Analysis:
  Receiver Operating Characteristic (ROC) curves are plotted to evaluate overall model effectiveness. The results of the confusion matrix analysis are illustrated in Figure 4.

IV. RESULTS AND DISCUSSIONS

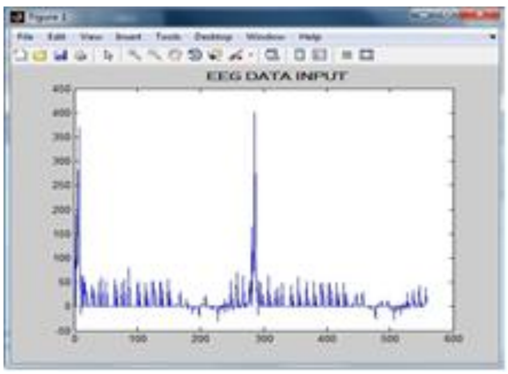

Figure 4: Raw EEG data input for the proposed model.

Figure 4 depicts the raw EEG signals as they are introduced into the proposed brainwave analysis framework.

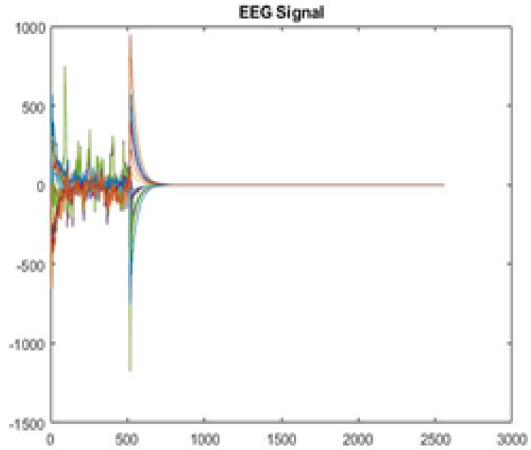

Figure 5: EEG spectrum after Discrete Wavelet Transform (DWT) processing.

Figure 5 illustrates the EEG spectrum obtained following the application of the DWT method.

The ResiNet configurations within the training toolbox are illustrated, with performance assessed using mean squared error (MSE). Training is conducted for up to 1000 epochs, though the actual number may vary based on data complexity, potentially extending the training duration. Validation is performed with a maximum of six checks to monitor and prevent overfitting. Gradient values are used to adjust the scaling factor of the analysis window, which ranges from 0 to 0.5, exploring various intermediate values throughout the training process.

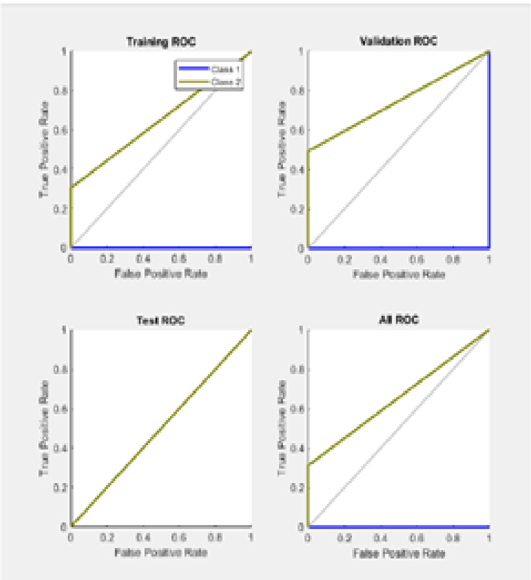

Figure 7: ROC curve illustrating the performance of the proposed LPRN model.

SN	INPUT DATA	REFERENCE	METHOD	EMOTION CATEGORIES	ACCURACY
1	EEG, PPG	E. H. Kim et al. (2020)	ConvLSTM	Arousal, Valence, Dominance	82.6%
2	EEG	Lin et al. (2022)	DCNN	Like/Dislike, Dominance, Familiarity	92.50%
3	EEG	Proposed Method	DCNN	Happy, Sad, Disgust, Abnormal	96.60%

Table 1 provides a comparative analysis of existing emotion recognition systems. The first method integrates EEG and PPG signals and utilizes a conventional LSTM model, achieving an accuracy of 82.6%. The second approach uses only EEG data and applies a Deep Convolutional Neural Network (DCNN), effectively classifying various emotional states such as like/dislike, dominance, and familiarity, with an accuracy of 92.50%. The proposed method, which also relies solely on EEG data and employs a Long-term Pattern Recognition Network (LPRN), outperforms the existing models by achieving an accuracy of 96.60%.

V. CONCLUSION

Depression is a growing mental health concern affecting a significant portion of the population. This work proposes a case-based reasoning approach for detecting depressive states using EEG signals acquired through a mobile three-electrode EEG device. The collected data undergoes preprocessing to remove artifacts and extract relevant features. The proposed system utilizes a Linear Pattern Recognition Network (LPRN) as the classification model. Prior to classification, a wavelet transform is applied to the EEG signals to extract frequency-based statistical features essential for emotion recognition. The model achieves a high classification accuracy of 96.60%, as validated through confusion matrix analysis. In addition to identifying depressive patterns, the system interprets emotional states from EEG data and generates music recommendations tailored to the user's detected mood.

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