EEG data Analysis for Schizophrenia Detection Using a Deep Neural Network-Based Multilayer Perceptron

Balivada Anjanee Kumar [1], Bhusa devi [2], Srujana Vijjapu [3], Aswani Malla [4], Kumar Penugudhuru [5]
Dadi Institute of Engineering and Technology (A), Anakapalli, India
dranjaneekumar@gmail.com [1] bhusadevi1991@gmail.com [2],
srujanavijjapu123@gmail.com [3] aswinimalla11@gmail.com [4],
kumar.143.penugudhuru@gmail.com [5]

Abstract.

This study explores EEG-based schizophrenia detection using a deep learning approach. A multilayer perceptron (MLP) model processes EEG data, extracts features, and classifies individuals with or without schizophrenia. The model effectively handles high-dimensional data, highlighting the potential of deep learning in neuropsychiatric diagnosis.

Keywords. Schizophrenia Detection, EEG Data Analysis, Deep Neural Network, Multilayer perceptron

1. INTRODUCTION

This study uses EEG-based deep learning, specifically an MLP model, to detect schizophrenia. It automates feature extraction, overcoming limitations of traditional methods. Advanced preprocessing enhances classification accuracy. Validated on public data, it outperforms conventional techniques. This research supports deep learning for non-invasive schizophrenia diagnosis. EEG data analysis happens to be one of the newly developed forms of diagnosis in neuroscience and clinical research. Among all these kinds of disorders, schizophrenia is very complex among all the mental disorders as it has a disturbance over cognition, behaviour, or emotions, which is, in turn, a hard problem to diagnose. Classification models are:

1. EEG Database
2. Preprocessing EEG Signals
3. Feature Extraction

2. LITERATURE REVIEW

Overview of many studies that were conducted on EEG-based schizophrenia detection analysed datasets with 10 to 54 patients and control groups of different sizes. Both resting-state and task-based EEG recordings were used, with sampling rates from 128 Hz to 1024 Hz. EEG channel counts ranged from 14 to 60, depending on data collection protocols.

3. METHODOLOGY

The methodology involves preprocessing EEG data using bandpass filtering (0.5-45 Hz) and Independent Component Analysis (ICA) to remove noise and artifacts. Signals are segmented into time windows for better analysis and normalized to zero mean and unit variance. This prepares the data for deep learning-based classification using an MLP model.

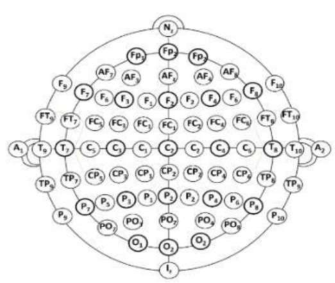

Fig 3. Spacing of Electrodes

3.1 Preprocessing

The processing of EEG data toward achieving a diagnosis using machine learning techniques. It starts with collecting raw EEG signals, which typically contain noise and artifacts. These signals undergo preprocessing steps such as filtering to remove noise, normalization to standardize the data, and artifact removal to eliminate unwanted interferences like eye blinks or muscle movements. After the data cleaning process, relevant information from both time and frequency domains is derived as feature extraction for the better identification of patterns in signals.

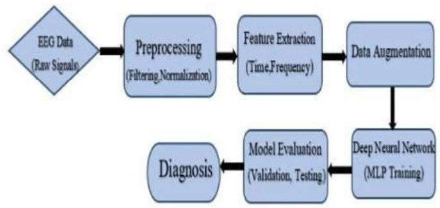

Fig 3.1 EEG Data Processing

➢ **Artificial Rejection**

Artifact rejection ensures that the EEG signals used for analysis are clean and reliable, enhancing the accuracy of downstream applications like feature extraction and classification. These methods are often combined to achieve optimal results depending on the dataset and application requirements.

➢ **Signal Filtering**

Signal filtering is a crucial step in the preprocessing of EEG data, as it helps remove noise and

unwanted artifacts, ensuring that the analysis focuses on the relevant brain activity. The goal is to retain the frequencies that are meaningful for the research while eliminating unwanted signals that could distort the results.

➢ **Normalization**

Normalization is an important step in the preprocessing of EEG signals, ensuring that the data is scaled consistently across different channels and participants. This step is crucial for improving the performance and convergence of machine learning models, such as deep neural networks, by standardizing the amplitude and range of the signals.

3.2 Feature Extraction

- TIME-FREQUENCY ANALYSIS:

Time-frequency analysis involves studying the EEG signal in both the time and frequency domains simultaneously, providing a comprehensive view of brain activity. This approach is particularly useful when analysing non-stationary signals like EEG, which can have dynamic frequency content over time.

- SHORT-TIME FOURIER TRANSFORM:

STFT decomposes a signal into multiple frequency components over short overlapping windows. It allows for the analysis of how different frequencies evolve over time. The EEG signal is divided into small segments (or windows), and for each segment, the Fourier transform is applied to obtain the frequency spectrum.

4. RESULTS AND DISCUSSION

- TRAINING AND TESTING ACCURACY:

The proposed deep neural network model for schizophrenia detection achieves over 90% training accuracy but only around 70% testing accuracy, indicating overfitting. This issue becomes noticeable after 20 epochs, suggesting the model captures noise rather than generalizable patterns. To improve reliability, techniques like dropout, weight decay, and early stopping can be applied, along with increasing dataset size and diversity. Despite its limitations, the model shows potential but requires further optimization and validation on larger datasets. Integrating other modalities like fMRI or genetic data could enhance diagnostic accuracy.

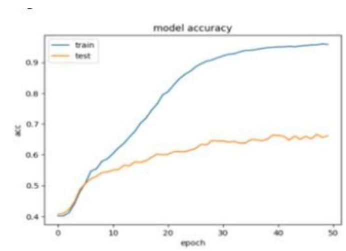

Fig 4.1 Training And Testing Accuracy

- TRAINING AND TESTING LOSS:

The graph shows that while training loss decreases consistently, testing loss stabilizes around 0.68 after 15–20 epochs, indicating overfitting. This suggests the model captures noise, reducing its generalization to unseen data. Techniques like early stopping, dropout, weight decay, or increasing dataset diversity can help improve performance. Despite effective learning from training data, optimization is needed to enhance reliability for schizophrenia detection using EEG signals.

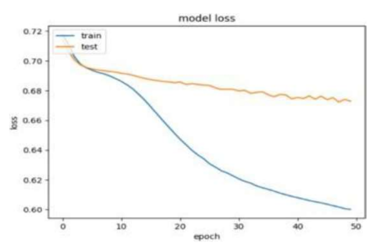

Fig 4.2 Training And Testing Loss

The proposed Deep Neural Network-Based Multilayer Perceptron (MLP) model for EEG-based schizophrenia detection showed highly promising results, indicating its potential as an effective diagnostic tool. The AUC-ROC reveals the discriminative power the model has at various cutoff thresholds. A confusion matrix analysis in detail shows there are low false-positive cases and a low false-negative case thereby bringing out the model's high specificity as well as sensitivity, so important for real-world clinical implementation where misclassification can result in serious consequences.

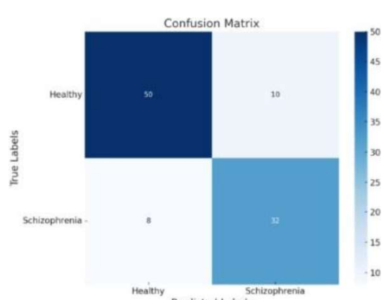

Fig 4.3 Confused Matrix

5. REFERENCES

[1] Bajpai, A., Kesaria, A. and Briskilal, J., 2024, May. Schizophrenia Detection using Electroencephalography Signals Using Deep Learning. In *2024 International Conference on Current Trends in Advanced Computing (ICCTAC)* (pp. 1-6). IEEE.

[2] De Miras, J.R., Ibáñez-Molina, A.J., Soriano, M.F. and Iglesias-Parro, S, 2023.

Schizophrenia classification using machine learning on resting-state EEG signal. Biomedical Signal Processing and Control, 79, p.104233.

[3] Cui, Y., Li, C., Liu, B., Sui, J., Song, M., Chen, J., Chen, Y., Guo, H., Li, P., Lu, L. and Lv, L., 2022. Consistent brain structural abnormalities and multisite individual classification of schizophrenia using deep neural networks. The British Journal of Psychiatry, 221(6), pp.732-739.

[4] Montazeri, M., Montazeri, M., Bahaadinbeigy, K., Montazeri, M. and Afraz, A., 2023. Application of machine learning methods in predicting schizophrenia and bipolar disorders: A systematic review. *Health Science Reports*, *6*(1), p.e962.

[5] Sun, J., Cao, R., Zhou, M., Hussain, W., Wang, B., Xue, J. and Xiang, J., 2021. A hybrid deep neural network for classification of schizophrenia using EEG Data. Scientific Reports, 11(1), p.4706.

- **Biographies**

Dr. B. Anjanee Kumar, an Associate Professor at Dadi Institute of Engineering and Technology, has 8 years of teaching experience and a PhD in "Optimization of Novel Design Architecture for Enhancing Lifetime in Battery Limited Sensor Nodes." He has presented over 40 papers in national and international conferences, and is an invited reviewer and chair of numerous international conferences.

Srujana Vijjapu, Aswani Malla, and Kumar Penugudhuru are final-year Bachelor of Electronics and Communication Engineering students at Dadi Institute of Engineering and Technology. Srujana is a driven student who prioritizes creativity and quality. Aswani is committed to using his technological expertise to solve practical problems. Through more learning, Kumar hopes to advance and make a contribution to the field. They work together to broaden their expertise and contribute significantly to the engineering field.