International Journal for Multidisciplinary Research (IJFMR)

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Ai Oriented System to Identify Type of Epilepsy Seizure Using Eeg Wave

Dr. K. Rama[1], Karlakunta Vamshi[2], Mikkilineni Pradeep[3], Chatla Vinay Kumar[4]

[1]IQAC Coordinator, Loyola Academy
[2,3,4]Student, Loyola Academy

ABSTRACT

For practical purposes, over the past three decades, several methods have been devised to mitigate various anomalies within corrupted EEG data. Nonetheless, there is still no universally acclaimed technique, rendering the field of study both intriguing and challenging. This research delves comprehensively into the identification and elimination of artifacts originating from ocular, muscular, and cardiac sources, offering a detailed analysis of their respective advantages and drawbacks. Furthermore, this investigation encompasses the methodologies employed for comparing real EEG data with simulated counterparts, serving to authenticate their efficacy. The primary focus of this work is twofold: firstly, to establish standardized criteria for the validation of recorded EEG signals in forthcoming studies, and secondly, to amalgamate diverse techniques through multiple processing stages, thereby facilitating the effective eradication of interference stemming from artifacts.

Keywords: Resolution, EEG, Artifacts, techniques, Validate.

1. INTRODUCTION

It's important to properly credit and cite sources when using information from external texts. Functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIRS), and electroencephalogram (EEG) are a few non-invasive neuroimaging techniques that are emerging as important tools for exploring and comprehending the functionality and dynamics of the brain. EEG stands out due to its non-invasiveness, mobility, affordability, and excellent temporal resolution EEG measures the collective electrical activity of a population of neurons, typically with amplitudes on the scale of a few microvolts. It finds applications across various disciplines, including neuroscience, psychology, cognitive science, and psychophysiology research [1–5]. Moreover, EEG is extensively employed in clinical research for diagnosing and detecting various brain illnesses such as sleep disorders, depression, epileptic activity, dementia, Alzheimer's disease, and schizophrenia [6–8]. The encephalogram, often referred to as the EEG, is the graphical representation of the brain's electrical activities. The complexity of the brain's electrical activity surpasses that of a single nerve fibre or neuron due to the involvement of numerous neurons and synapses. The systematic analysis of EEG waves was pioneered by German psychiatrist Hans Berger, leading to the term "Berger waves" being associated with EEG patterns. EEG's utility extends to the diagnosis of neurological disorders and sleep disorders [1–5].

2.Existing system

In an era where the fusion of neuroscience and technology is reshaping the boundaries of human-computer interaction, Electroencephalography (EEG) stands at the forefront as a versatile and accessible tool. As the demand for Brain-Computer Interface (BCI) systems continues to grow, the significance of EEG cannot be overstated. Its portability and simplicity make it a key enabler, facilitating seamless communication between the human mind and machines. Techniques were created based on the most recent machine learning-based categorization of bivariate patterns. An EEG crid based one is an easy-to-use array made up of 10 electrodes positioned close to the ear. Unusual sensory gating is the key mechanisms in schizophrenia to examine the impact of auditory sensory gating on the dynamical complexity of brain activity in schizophrenia as compared to normal control groups. In the marker-controlled watershed segmentation technique, it separates the touching objects in the image to provides best identification of the main edge of the image and avoids over segmentation [9]

3.Proposed system

The proposed system employs a widely used method to remove artifacts from EEG data: regression analysis. It utilizes one or more reference channels to detect these artifacts within EEG signals. By estimating artifact propagation coefficients, the system subtracts these artifacts from the EEG data, forming the basis for regression techniques. This process often involves using electrooculography (EOG) signals for ocular artifacts and electrocardiography (ECG) data for ECG artifacts as reference signals. The primary benefit of this approach is effective artifact removal and segment rejection.

2.1Block diagram

In the present study the various stages for EEG signal wave investigation is done as shown in the figure 3.1.

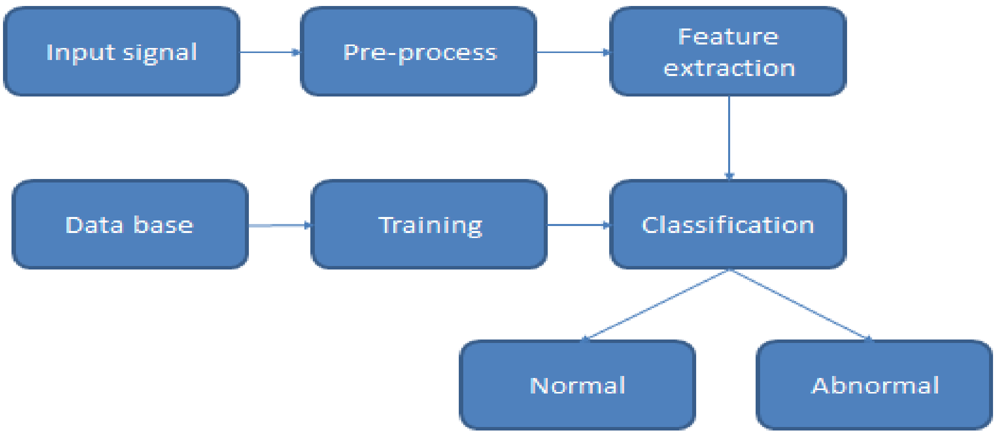

Figure 3.1. Architecture of EEG Signal Process

a) Profound states, Information Assortment and Arrangement:

1. Place electrodes and sensors correctly on subjects.
2. Ensure proper electrode positioning and impedance checks.
3. Record data while subjects engage in various tasks or during rest.
4. Segment the data into periods of interest or specific tasks.

5. Store the data in a suitable format for analysis.

These steps are crucial for collecting high-quality EEG data for research or clinical purposes.

b) Signal Preprocessing:

1. Implement filtering methods such as high-pass and low-pass filters to eliminate drift and noise.
2. Employ notch filtering to eliminate power line interference (e.g., 50/60 Hz).
3. Utilize Independent Component Analysis (ICA) to remove artifacts like eye blinks and muscle activity.
4. Apply referencing methods, such as common referencing, to reduce noise and enhance data quality.

These strategies are essential for preprocessing EEG data to ensure accurate analysis and interpretation.

c) Highlight Extraction:

1. Compute time-domain features:
    a. Calculate statistical measures like mean, variance, skewness, and kurtosis of the EEG signal.
    b. Determine Root Mean Square (RMS) values.
2. Compute frequency-domain features using methods like Fast Fourier Transform (FFT):
    a. Analyse power spectral density in different frequency bands (e.g., delta, theta, alpha, beta, gamma).
    b. Identify dominant frequencies and spectral entropy.
3. Explore time-frequency analysis techniques:
    a. Utilize methods such as Wavelet Transform or Short-Time Fourier Transform to capture time-varying frequency information.

These feature extraction techniques help in characterizing EEG data for further analysis and interpretation, providing valuable insights into brain activity.

d) Recognizable proof of EEG Signal Waves:

1. Segment EEG data into shorter time windows for a more detailed examination of various frequency components.
2. Apply bandpass filters to isolate specific frequency ranges (e.g., delta, theta, alpha, beta, gamma) of interest.
3. Identify and characterize each wave's features within the segmented data, including:
    - Peak frequency
    - Amplitude
    - Duration
    - Distribution across electrodes

These steps enable a finer-grained analysis of EEG signals, helping to uncover specific patterns and characteristics associated with different brain activities and states.

e) Measurable Investigation and Perception:

1. Conduct statistical tests to compare different conditions or subjects, assessing the significance of EEG differences.
2. Create visual representations to illustrate the distribution of various EEG waves, including:
    - Power spectral density plots to show the frequency characteristics.

- Scalp topography maps to display the spatial distribution of EEG activity across the scalp.
- Time-frequency plots to highlight wave dynamics over time.

These visualizations and statistical analyses help in interpreting EEG data and understanding the variations in brain activity under different conditions or among different subjects.

f) Application-Explicit Examination:

1. Brain-Computer Interfaces (BCIs): Train classifiers to decode mental states or movements from EEG patterns.
2. Mental State Recognition: Correlate wave patterns with mental tasks or states.
3. Neurological Disorder Diagnosis: Identify abnormal wave patterns associated with disorders.
4. Sleep Monitoring: Analyse transitions between different wave states during sleep cycles.

These applications leverage EEG data to enhance brain-related research, diagnostics, and brain-computer interaction technologies.

g) Approval and Understanding:

Interpret the results in the context of your research objectives and the physiological basis of EEG waves. This step ensures that your conclusions are consistent with established scientific understanding and contributes to the broader field of EEG signal analysis and neuroscience.

h) Conversation and End:

Discuss the significance of observed wave patterns and their implications.

Summarize how your findings contribute to the broader field of EEG signal analysis, emphasizing their relevance and potential applications.

Highlight limitations in your study and suggest directions for future research. Identifying constraints and proposing areas for further investigation helps advance the understanding and utilization of EEG data.

i) Moral Contemplations:

Ensure the security and informed consent of participants, prioritizing their well-being and privacy. By following these ethical principles, researchers can effectively investigate EEG signal waves to gain insights into brain activity patterns, mental processes, and various applications while upholding ethical standards and participant rights.

4. Deep Learning Algorithm

The study of EEG waves involves several key steps:

Step 1: Implement the discrete wavelet transform (DWT), which decomposes the signal into a discrete set of wavelet scales and translations following defined rules.

Step 2: Distinguish DWT from the continuous wavelet transform (CWT) by decomposing the signal into mutually orthogonal sets of wavelets, a key difference from the CWT or its discrete-time counterpart (DT-CWT).

Step 3: Construct wavelets using scaling functions that define their scaling properties. The requirement for these scaling functions to be orthogonal to their discrete translations imposes specific mathematical conditions, such as the dilation equation.

$$\phi(x) = \sum_{k=-\infty}^{\infty} a_k \phi(Sx - k).$$

-------Equation (Eq 4.1)

Step 4: Include a scaling factor, typically chosen as 2. Ensure that the area beneath the function is normalized, and the scaling function remains orthogonal to its integer translations.

Step 5: Introduce additional conditions since the previous restrictions do not yield a unique solution. These additional conditions lead to results, including a finite set of coefficients (a_k) that define the scaling function and the wavelet. The wavelet is derived from the scaling function as part of this process.

$$\psi(x) = \sum_{k=-\infty}^{\infty} (-1)^k a_{N-1-k} \psi(2x - k)$$

--------Equation (Eq 4.2)

Step 6: Use an even integer (n) to further define the wavelet. The set of wavelets derived in this manner constitutes an orthonormal basis, which is employed to decompose signals. Typically, only a small number of coefficients (a,k) are non-zero, simplifying the calculations involved in the decomposition process.

5.RESULTS

MATLAB software is used to analyse EEG signals. Open MATLAB software and go to code location from their copy of the code path. Open the current folder of the chosen path. On the screen there is script mode code and down on it there is a command window. In the command window the input and output features are displayed.

a) Process

Select the script mode file then double click on MAIN.M then it opens on script mode. Then click on the run button.

By user interface it will open a small mini-interface, from there select the needed excel sheet as shown in the figure 5.1.

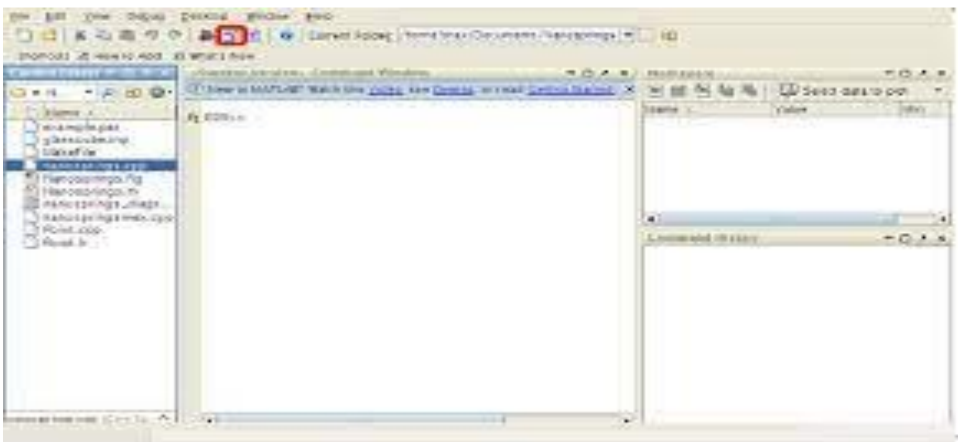

Figure 5.1. Opening an interface

Compare input feature values using algorithms. It will show some graphical representations with the help of interface code as shown in figure 5.2.

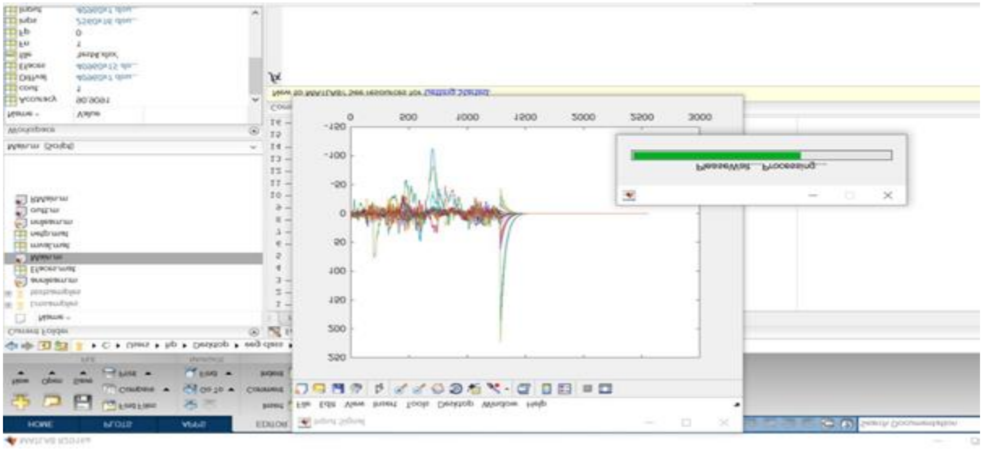

Figure 5.2. Graphical representations using interface code.

In and learnit has Database features. In and learn code Database features are trained up by Neural network algorithm. Then it will be noted into the main program.it will be stored in a particular variable.

1. Database features are stored in one variable.
2. The input signals are stored in another variable.

Through simulation, comparison of both database and input signals {count = sim (netp, Features). Types of conditions are noted.

By combining both database and input features then it gives accurate level results.

Results will be shown according to the condition given in the code as shown in the figure 5.3.

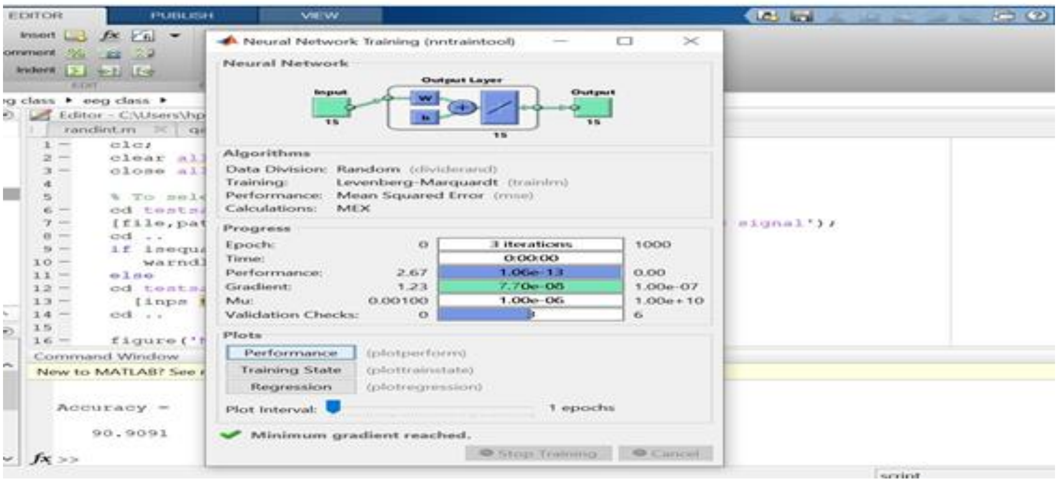

Figure 5.3. Validation of input

The EEG signal analysis process involves evaluating performance, assessing the training state, and conducting regression. According to figure 5.4. There are three graphs:Gradient, mu, validation. plotting the gradient values, mu and validation fail. Gradients represent slope of tangent of graph of function. It points to the direction in which there is a high rate of increase for the considering function. 'mu' is the control parameter for the back-propagation neural network that we modelled, and choice of mu directly affects the error convergence. Validation check is used to terminate the learning of neural networks. The number of validation checks will depend on the number of successive iterations of the neural network.

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

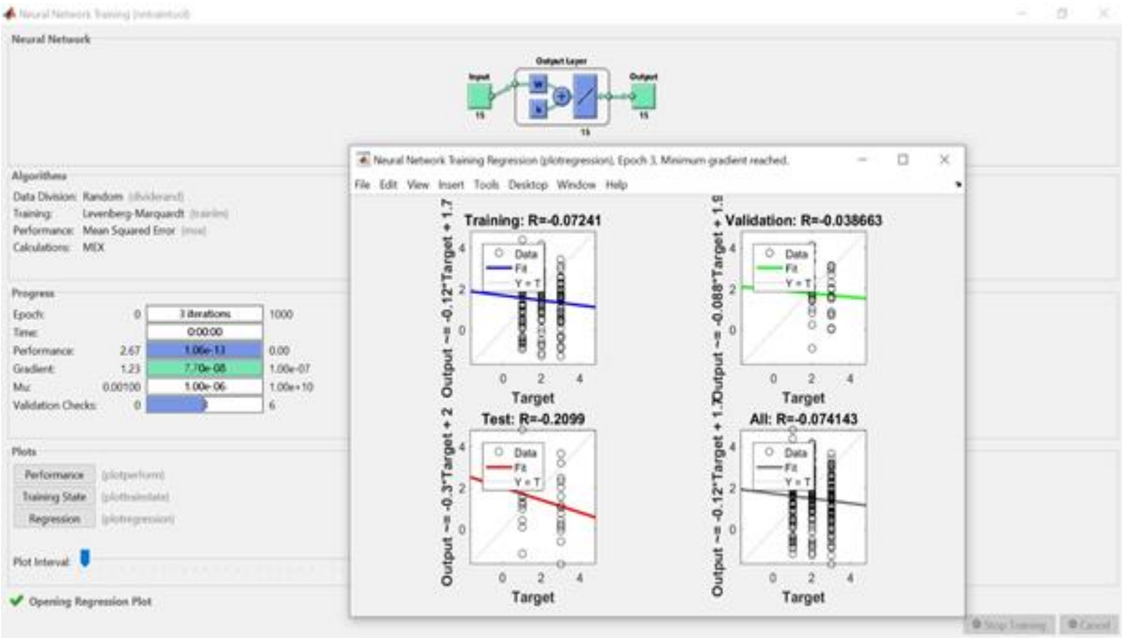

Figure 5.4. Target outputs

According to the graph there are a total of 4 target outputs.

1. **Training Target:** These are the known correct outcomes or labels for the EEG signals in the training dataset. The deep learning model uses them during training to learn and make accurate predictions based on input EEG data.
2. **Validation Target:** Like training targets, validation targets contain correct outcomes or labels for EEG signals. They are reserved exclusively for evaluating the model's performance during hyperparameter tuning. This helps assess how well the model generalizes to unseen data and prevents overfitting.
3. **Test Target:** Test targets represent the correct outcomes or labels for EEG signals in the test dataset. These labels are kept separate from the model during training and validation. After training and hyperparameter tuning, the model's real-world performance is assessed using the test target. It gauges the model's ability to generalize to new, unseen EEG signals.
4. **All Target Output Graph:** While not a standard term, this likely refers to a graphical representation showing the model's predicted outputs (predictions) compared to the actual target values across all samples in a dataset (training, validation, or test).

- **X-Axis:** Represents the samples (e.g., EEG signal segments or instances) in the dataset.
- **Y-Axis:** Represents either the predicted values generated by the model or the actual target values (labels).
- **The graph** visually compares the model's predictions with the true target values. Ideally, data points on the graph should align closely with the diagonal line (y = x), indicating that the model's predictions match the true targets.

This analysis helps assess the model's accuracy and how well it aligns with the expected outcomes across different sets of data.

6.Conclusion

The method described involves conducting numerous comparisons, particularly between the original EEG data and simulated EEG waves. The analysis focuses on four target outputs, and graphical verification is employed to achieve more robust comparison results. To summarize:

- **Training Target, Validation Target, and Test Target:** These are distinct sets of labels used for various stages of deep learning model development when working with EEG signals. The training target aids in model training, the validation target helps fine-tune the model's hyperparameters, and the test target assesses the model's real-world performance.
- **All Target Output Graph:** This visualization represents a comparison between the model's predictions and the true target values across all data samples. The alignment of these predictions with the true targets, as indicated by their proximity to the diagonal line (y = x), is crucial for evaluating the model's accuracy and generalization capabilities. By utilizing these targets and graphical comparisons, researchers and practitioners can assess the effectiveness of deep learning models in processing EEG data and making accurate predictions, ultimately advancing the field of EEG signal analysis.

References

1. Saeid Sanei and J. A. Chambers, "*EEG Signal Processing*", John Wiley and Sons Ltd., Online ISBN:9780470511923, First Edition, Ch. 1, p1 – p18, September 2007.
2. B. Obermaier, G. R. Müller and G. Pfurtscheller," *Virtual Keyboardcontrolled by Spontaneous EEGActivity*", IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol. 11, No. 4, p422 – p426, December 2003
3. Rajesh Singla, Balraj Gupta, *"Brain Initiated Interaction"*, Journal of Biomedical Science and Engineering, ISBN: 978-988-17012-9-9 ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)p170 – p172, 2008.
4. Sovierzoski M.A., Argoud F.I.M., de Azevedo F.M., *"Identifying eye blinks in EEG signal analysis "*, Proceedings of the 5th International Conference on Information Technology and Application in Biomedicine,ISSN NO:1001-2400, p406 - p409, May 2008, China.p406 - p409, May 2008, China.
5. D. G. Manolakis, V. K. Ingle, S. M. Kogon, "*Statistical and Adaptive Signal Processing: Spectral Estimation, Signal Modeling, Adaptive Filtering and Array Processing",* Artech House Publishers, 2005. ch. 3, pp. 75–82.
6. Manoilov, P. P. *"EEG Eye-Blinking Artifacts Power Spectrum Analysis"*, Proceedings of International Conference on Computer Systems and Technologies, CompSysTech '06, V. Tarnovo, Bulgaria, 15-16 June 2006, pp. IIIA.3-I-IIIA.3-5.
7. Guido Dornhege, José del R. Millán, Thilo Hinterberger, Dennis J. McFarland Dennis J. McFarland,Klaus-RobertMüller,*"TowardBrain-ComputerInterfacing"*, ISBN:9780262527880First Edition, The MIT Press.
8. Steven G. Mason, Gary E. Birch, *"A General Framework for Brain– Computer Interface Design"*, IEEE Transactions on Neural Systems and Rehabilitation Engineering, Print ISSN: 1534-4320, Electronic ISSN: 1558-0210 Vol. 11, No. 1, March 2003.
9. Bhamidi Rama, I.V. Subba Reddy,K.Jeevana, D. Mary Shamily published a paper on "Lung Cancer detection by Using Marker-ControlledWatershed Transform and K-means Clustering" in an

international journal &magazine of enggneering and technology,management and research ISSN no.2348-4845 vol 3 2016,issue no.5 may,www.ijmetmr.co.