

A Dynamic Graph Neural Network-Based Framework for EEG Signal Classification in Eye State Detection

S. Prakash³

³Assistant professor, Department of Electrical and Electronics Engineering,
Aarupadai Veedu Institute of Technology, Vinayaka Missions Research Foundation,
Chennai, India - 603104. prakash.yours@gmail.com

Corresponding Author E-mail:

ABSTRACT: Accurate Eye State Detection (ESD) from Electroencephalogram (EEG) signal are important for understanding human visual attention, monitoring cognitive states, and developing intelligent human-computer interaction systems. However, EEG signals are highly nonlinear, non-stationary, in addition susceptible to noise, outliers, and temporal variations for ESD challenging. To overcome these issues, this paper proposes a Dynamic Graph Neural Network (DGNN)-based framework for EEG signal classification in ESD. The collected EEG eye-state dataset thereby a pre-processing based on data cleaning is executed to eliminate inconsistent samples, outlier removal to reduce the influence of abnormal signal observations. Z-score normalization is applied to standardize the EEG features and provide a consistent input distribution for subsequent learning. The normalized EEG signals are divided into temporally meaningful segments using a sliding-window segmentation technique. The segmented EEG data are then transformed into a dynamic graph representation, where EEG signal features are modelled as graph nodes and their relationships are represented through graph edges. The proposed DGNN performs graph-based feature learning by aggregating information from interconnected nodes whereas considering their changing relationships. The experimental outcome is implemented in Python software using EEG eye state dataset have the higher accuracy of 95.6%, precision of 95.4%, recall of 94.5%, F1-score of 98%, AUC of 99.2 and Cohen kappa of 0.91 using proposed DGNN for EEG signal classification in ESD. The proposed DGNN provide an effective representation of the complex spatiotemporal characteristics of EEG signals and improve the reliability of eye state classification.

Keywords: Eye State Detection, Electroencephalogram, Dynamic Graph Neural Network, Sliding-Window segmentation, Dynamic Graph Representation.

1. Introduction

EEG signals is an important role in brain works and its activity influences cognitive abilities, motor functions, and sensory processing [1-2]. EEG is a technology for brain-computer interface (BCI) applications [3]. Consequently, for evaluating these classifiers is to use EEG signals recorded however subjects is either resting with their Eyes Closed (EC) or Eyes Open (EO) [4]. These two conditions are widely used because

their EEG patterns which are relatively easy to distinguish, suitable for testing classification methods [5-6]. The main differences between the EC and EO states are the presence or absence of eye-blink activity and changes in the alpha-frequency power of the EEG signals [7]. Researchers have developed various methods to classify brain activity recorded through EEG.

2. Related Work

Several techniques are utilized for EEG signal classification in ESD. In [8] Jawed et al (2024) have proposed Long Short Term Memory–Convolutional Neural Network (LSTM-CNN) to categorize EEG signals for ESD. CNN extracts local EEG patterns, whereas LSTM learns time-dependent information. However, performance decreases when the training dataset is small. Consequently, in [9] Kode et al (2024) have presented One-Dimensional Convolutional Neural Network (1D-CNN) to features directly from EEG signals for ESD. 1D-CNN identify local patterns and temporal variations in EEG signals. Nevertheless, choosing the suitable kernel size, number of layers, learning rate, and other parameters remain time-consuming. Additionally, in [10] Bashir et al (2025) have developed a K-Nearest Neighbors (KNN) classifier, which identifies the disease category. It stores the training samples and performs classification when a new sample is specified. Nonetheless, noisy EEG features reduce classification accuracy. Furthermore, in [11] Khalfallah et al (2025) have invented Support Vector Machines (SVM), CNN and ChronoNet from EEG recording of different neurological conditions. However, requires greater computational resources and training time. Moreover, in [12] Alghamdi et al have presented eXtreme Gradient Boosting (XGBoost) algorithm, Kohonen’s Self-Organizing Map (SOM) with Hypergraph Partitioning Algorithm (HGPA) to classify EEG signals for ESD. It delivers an effective way to visualize and organize high-dimensional EEG data. Nevertheless, ensemble clustering and boosting processes increase training time. To overcome these limitations this papers propose a DGNN for EEG signal classification in ESD.

2.1 Research Contribution

The proposed DGNN framework is used for effective EEG-based eye-state classification. The spatiotemporal EEG characteristics are used to

improve the reliability of EO and EC state detection, it more suitable for the nonlinear and non-stationary nature of EEG signals.

3. Proposed Methodology

For accurate EEG signal classification in ESD, at first pre-processing based on data cleaning is implemented to remove inconsistent samples, whereas outlier removal minimizes the effect of abnormal EEG observations. The cleaned data are then fed to Z-score normalization to pass the EEG features into a common scale to improve signal quality. Following, the normalized EEG signals are fed to segmentation based on sliding-window technique it allows the variations in brain activity over time. Every segmented EEG sample is next converted into a dynamic graph structure, in which EEG signal features are represented as graph nodes and their relationships are modelled as graph edges. The proposed DGNN then learns discriminative spatiotemporal representations by aggregating information from interconnected nodes whereas dynamically adapting to changes in their relationships. At last, DGNN classify the EEG signals into the corresponding eye states, like EO and ES thereby improving the reliability of eye-state classification. The block diagram for the proposed structure is presented in figure 1.

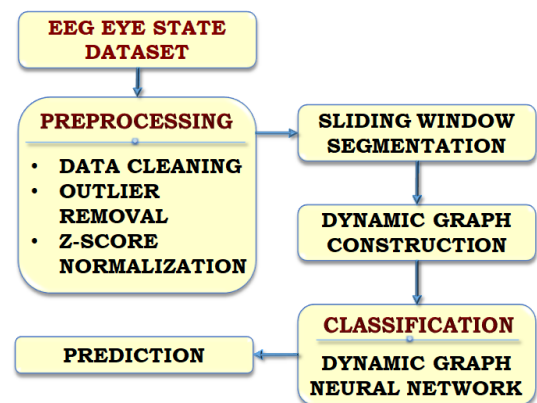


Figure 1: Proposed block diagram for ESD

3.1 Pre-processing

For accurate EEG signal classification in ESD, data cleaning is utilized to remove incomplete samples from the EEG eye state dataset, whereas outlier removal minimizes the effect of abnormal

EEG observations from the cleaned data. The cleaned data are then fed to Z-score normalization to get the EEG features into a common scale. It is expressed as

$$Z = \frac{X - \mu}{\sigma} \quad (1)$$

Wherever, X specifies original data point, μ signifies the mean, σ stands for standard deviation and Z indicates normalized value. The EEG signal is processed as the better quality signal for further segmentation. The processed EEG signal is fed to segmentation based on sliding window.

3.2 Segmentation by Sliding Window

The sliding window technique segments the continuous EEG signal into a sequence of overlapping temporal windows. EEG signals are highly dynamic and their characteristics change over time, analysing the complete signal as a single sequence short-term changes related with EO and EC. The sliding window is expressed as

$$X_i = X[(i - 1)S : (i - 1)S + W] \quad (2)$$

Where W signifies the window length, S denotes the sliding step, and X_i represents the i^{th} EEG segment. Using the sliding window the EEG signal is segmented as EO and EC for further extraction. The segmented EEG signal is fed to dynamic graph construction.

3.3 Dynamic Graph Construction

For EEG signal classification in ESD every EEG sample is converted into a dynamic graph representation to clearly model the spatial and functional relationships among EEG channels. The EEG channels as independent signal sequences, graph-based modelling represents the EEG data as an interconnected structure, which is more suitable for capturing interactions between different brain regions. Each EEG channel is represented as a node in the graph. The constructed EEG signal is fed to classification based on DGNN.

3.4 Classification by DGNN

The proposed DGNN is appropriate for EEG signal classification in ESD because EEG signals contain both temporal variations and relationships among different EEG channels. A DGNN characterizes these relationships as a graph and dynamically change over time. EEG signal from N channels is represented as

$$G(t) = [g_1(t), g_2(t), \dots, g_N(t)] \quad (3)$$

Where $g_i(t)$ indicates the EEG signal recorded from the i^{th} channel at time t . The DGNN performs message passing among connected EEG nodes. Figure 2 shows the architecture of DGNN.

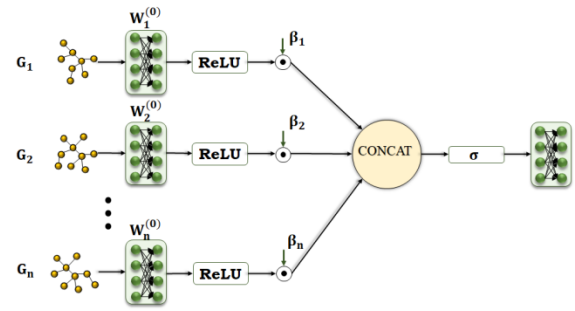


Figure 2: Architecture of DGNN

A graph aggregation operation is expressed as:

$$h_i^{(l+1)} = \sigma(\sum_{j \in N(i)} A_{ij}^t W^{(l)} h_j^{(l)} + b^{(l)}) \quad (4)$$

Where, $h_i^{(l)}$ is the representation of node i at layer l , $N(i)$ signifies the neighbouring nodes, A_{ij}^t denotes the relationship strength between nodes i and j , $W^{(l)}$ is a learnable weight matrix, $b^{(l)}$ denotes bias, σ indicates nonlinear activation function. The DGNN is capable of learning discriminative spatiotemporal features rather than relying only on static EEG characteristics. The proposed DGNN provides an effective classification form EEG signal for ESD.

4. Experimental Result and Discussion

In this section for EEG signal classification in ESD it is implemented in Python software using EEG eye state dataset with the dataset set for training is 9980 and testing is 5000. Total number of column used is 15 and dataset size after outlier removal is 9948. The class label are when the eye is open it is mentioned as class 0 and when the eye

is close it is mentioned as class 1. The number of input feature X is 14 thereby the features are AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 and the number of feature Y is mentioned as target.

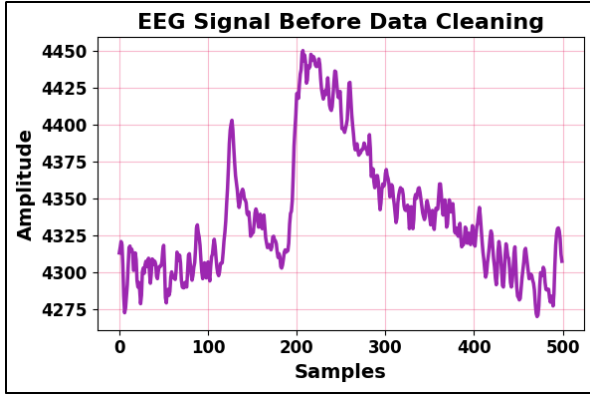


Figure 3: EEG signal before data cleaning

Figure 3 shows the EEG signal before data cleaning. Its amplitude values ranging unevenly from 4275 to 4450 over 500 sample points, displaying high-amplitude deflections around samples 120 and 200–250 before cleaning the data.

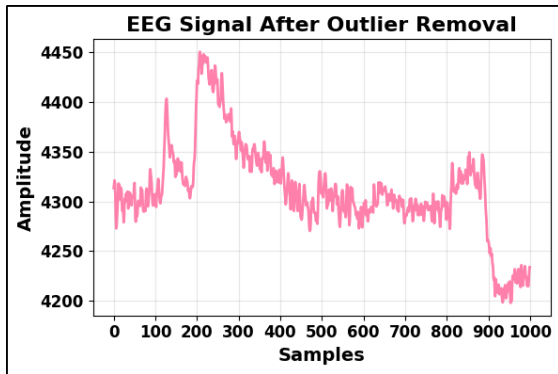


Figure 4: EEG signal after outlier removal

Figure 4 displays the EEG signal after outlier removal. There is a clear variation in the EEG waveform is observed near sample 120, followed by a broad elevation wave between samples 200 and 300 thereby a sudden drop occurs around sample 900, moving the signal baseline down to approximately 4200 after outlier removal from the cleaned data.

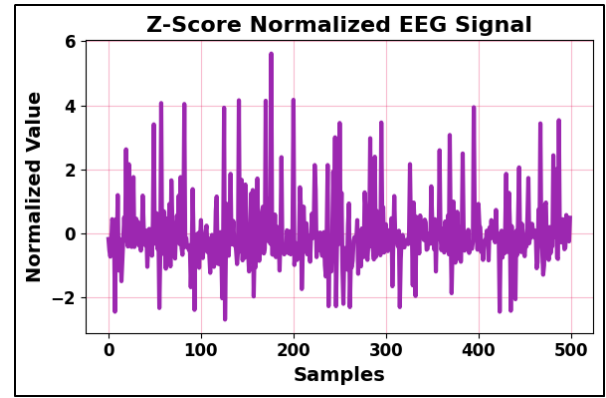


Figure 5: Z-score normalized EEG signal

Figure 5 shows the Z- score normalized EEG signal. The sharp upward and downward spikes exceed a z-score magnitude of 4, with the highest peak located near sample 180 nearly 6. Z-score normalization centers the mean amplitude at 0 and scales the variance; it is easier to spot high-amplitude noise in the time series from the EEG signal for further segmentation.

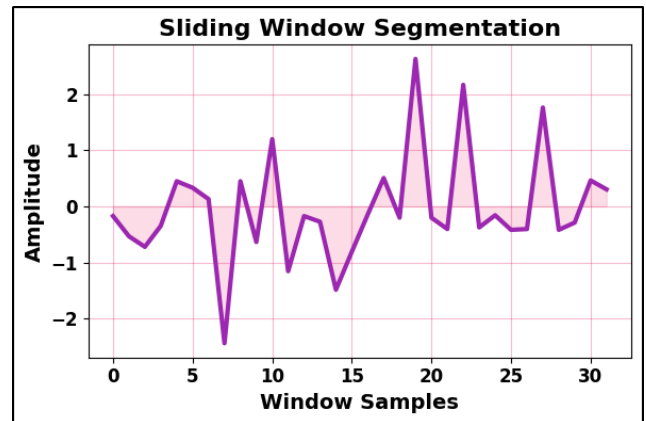


Figure 6: Sliding window segmentation

Figure 6 displays the sliding window segmentation. It plots an amplitude value which ranges from -2.5 to 2.6 against 32 window samples that is 0 to 31. Sliding window segmentation breaks a continuous sequential signal into smaller, overlapping, consecutive windows for EEG signal classification in ESD.

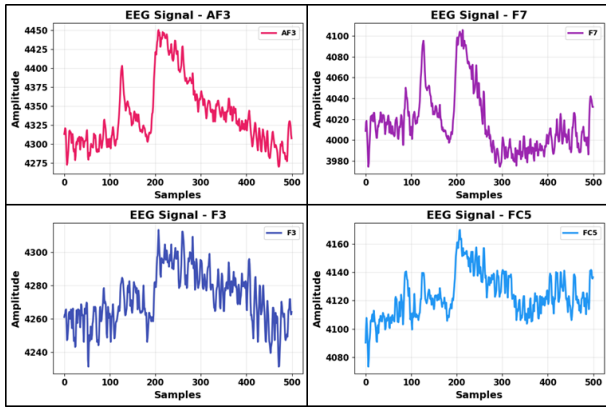


Figure 7: EEG signal features AF3, F7, F3 and FC5

Figure 7 shows the EEG signal features AF3, F7, F3, and FC5. Each feature displays a sharp, synchronized amplitude deflection near the 200-sample mark, indicating a peak variation in the brain wave using dynamic graph construction technique for further features.

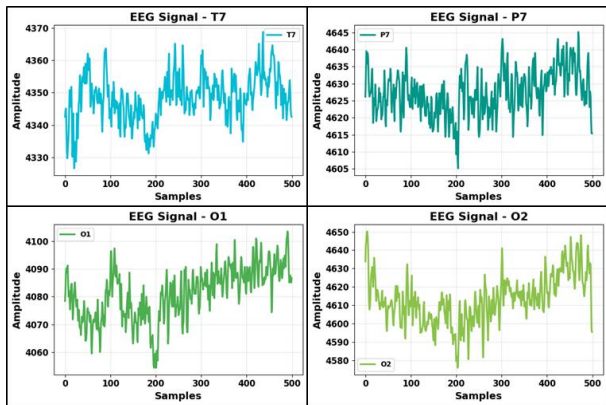


Figure 8: EEG signal features T7, P7, O1 and O2

Figure 8 displays an EEG signal features T7, P7, O1 and O2. The EEG time-series data for temporal plotted across 500 sample points on the horizontal axis and varying amplitudes on the vertical axis. The traces show continuous high-frequency fluctuations with downward signal drift near the 200-sample mark across the sections in the brain wave. This displays a fluctuation in other samples in the EEG signal.

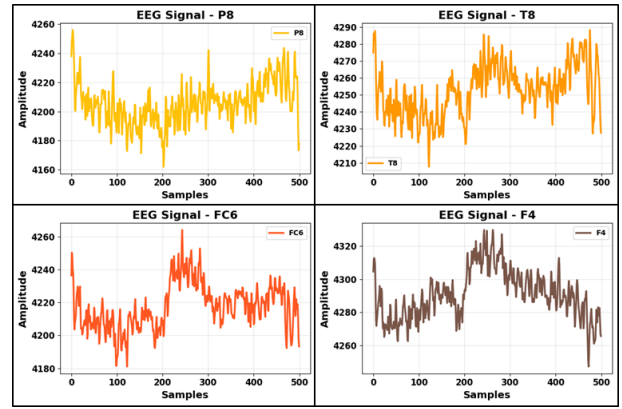


Figure 9: EEG signal features P8, T8, FC6 and F4

Figure 9 displays EEG signal features P8, T8, FC6 and F4. The horizontal axis signifies sample counts from 0 to 500, and the vertical axis shows amplitude values adjusted to a baseline range between approximately 4160 and 4330 units. The FC6 and F4 channels show a wide rise in amplitude values centered roughly between samples 200 and 300. The P8 and T8 channels show continuous, high-frequency oscillations and minor baseline throughout the 500 sample window without distinct singular peak in the brain wave for EEG signal classification in ESD.

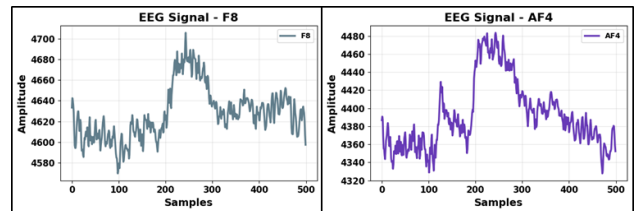


Figure 10: EEG signal features F8, AF4

Figure 10 displays the EEG signal features F8 and AF4. The F8 and AF4 features shows over 500 samples, both displaying a transient occurrence between samples 200 and 300; it indicates a clear variation in the EEG waveform is observed on 250 is a physiological brain wave.

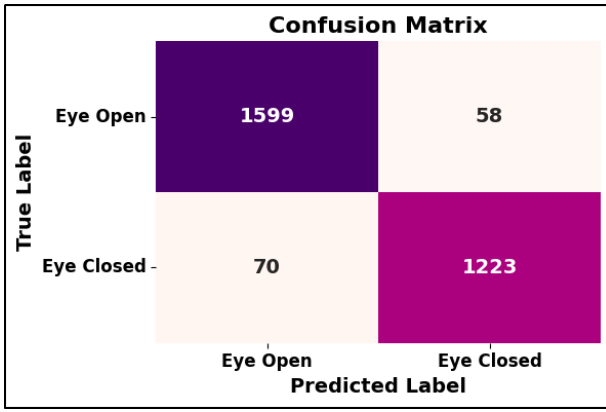


Figure 11: Confusion matrix using proposed DGNN

Figure 11 displays the confusion matrix. The eye open correctly predicted is 1,599; eye closed correctly predicted is 1,223. Predicted eye open, normally closed is 70 and predicted eye closed, normally open is 58, indicating an effective prediction using proposed DGNN for EEG signal classification in ESD.

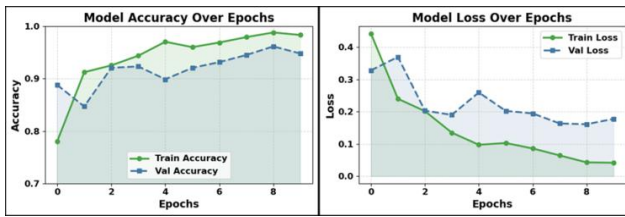


Figure 12: Model accuracy and loss over epochs

Figure 12 shows the accuracy and loss over epochs. The train accuracy steadily increases

toward 0.98, whereas the validation accuracy fluctuates around 0.92 to 0.95, representing stable and strong model performance. The train loss steadily decreases down close to 0.04. However, the validation loss stops improving after epoch 3, spikes at epoch 4, and stabilizes at a much higher level than the training loss, representing stable convergence and effective model learning.

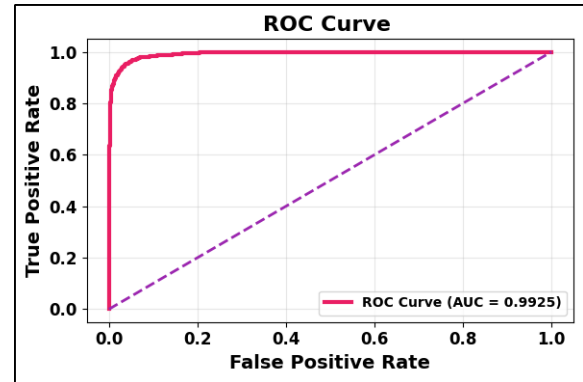


Figure 13: ROC curve

Figure 13 displays the ROC curve using proposed DGNN. The AUC value for the proposed DGNN is 0.992 which is high compared to the other existing techniques, indicating a stable convergence for EEG signal classification in ESD.

4.1 Comparison with the proposed technique

In the evaluation with proposed technique the proposed DGNN method is compared with the existing techniques as presented in table 1.

Table 1: Comparison with the proposed technique

Study	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC	Cohen kappa
Jiang et al [3]	87	91	80.7	85.7	87.2	0.63
Aksu et al [7]	71	-	-	-	92	0.63
Jawed et al [8]	94	92	80	94	-	-
Zhong et al [1]	95.2	95.3	94.3	94.8	-	-
Proposed Work	95.6	95.4	94.5	98	99.2	0.91

Jiang et al [3] have the accuracy of 87%, precision of 91%, recall of 80.7 %, F1-score of 85.7%, AUC of 87.2 and Cohen kappa of 0.63, Aksu et al [7] have the accuracy of 71%, AUC of 92 and Cohen kappa of 0.63, Jawed et al [8] have the accuracy of 94%, precision of 92%, recall of 80%, F1-score of 94.8%, Zhong et al [1] have the accuracy of

95.2%, precision of 95.3%, recall of 94.3%, F1-score of 94.8%, and the higher value with accuracy of 95.6%, precision of 95.4%, recall of 94.5%, F1-score of 98%, AUC of 99.2 and Cohen kappa of 0.91 using proposed DGNN for EEG signal classification in ESD.

5. Conclusion

DGNN framework is proposed for accurate ESD using EEG signals. During pre-processing, the raw EEG eye-state data are cleaned to remove inconsistent observations, outliers are removed, and the data are normalized to obtain a consistent representation. The EEG signals corresponding to EO and EC states are then divided into meaningful temporal segments using a sliding-window technique. These segments are subsequently represented as dynamic graphs to capture the relationships between EEG features and their changes over time. Furthermore, the DGNN effectively learns complex spatiotemporal patterns through graph-based feature aggregation, thereby improving the classification of eye states. Experimental evaluation is executed in Python software using the EEG eye-state dataset demonstrates that the proposed framework achieves an accuracy of 95.6%, precision of 95.4%, recall of 94.5%, F1-score of 98%, AUC of 99.2%, and Cohen's kappa of 0.91. The proposed DGNN accurately classifies the ESD in the early stage. The future work focuses on larger and more diverse EEG datasets collected from subjects with different ages, cognitive conditions, and recording environments to improve generalization.

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