Enhanced Depth of Anesthesia Classification Using Graph Neural Networks and EEG Features

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APPROVAL

This Thesis titled **"Enhanced Depth of Anesthesia Classification Using Graph Neural Networks and EEG Features"**, submitted by **Abdullah Al Mahmud,** ID No: **241-25-038** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of **M.Sc. in Computer Science and Engineering** and approved as to its style and contents. The presentation has been held on **24-05-2025**.

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I hereby declare that, this project has been done by me under the supervision of **Dr. Md. Zahid Hasan, Associate Professor, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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Finally, I must acknowledge with due respect the constant support and patients of my parents.

ABSTRACT

During surgical procedures, precise monitoring of the depth of anesthesia (DoA) is crucial for patient safety; yet, conventional techniques, such as the Bispectral Index (BIS), are expensive and opaque. Based on EEG signals from a dataset of 24 patient cases, this study suggests a unique method for classifying DoA into four states: general anesthesia, profound anesthesia/burst suppression, moderate sedation, and awake/light sedation. It does this by employing a Graph Neural Network (GNN). Before extracting features including spectral entropy, Hjorth parameters, and peak-specific metrics, the methodology preprocesses EEG data using bandpass filtering (1–50 Hz), DC offset removal, downsampling to 128 Hz, normalization, and smoothing. To represent feature interdependencies, a correlation-based graph was built. It outperformed more conventional models such as ANN (78.83%) and ResNet50 (62.75%) with a classification accuracy of 91.46%. With the potential to improve patient outcomes and accessibility in environments with limited resources, the open-source GNN paradigm provides a reasonably priced and interpretable substitute for proprietary solutions. Subsequent research will concentrate on verifying the model using bigger datasets and investigating the viability of real-time deployment.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Comparatively to imaging techniques like functional magnetic resonance imaging (fMRI) or positron emission tomography (PET), electroencephalography (EEG) is a non-invasive technique that captures the brain's electrical activity using scalp electrodes, so providing high temporal resolution and affordability. Monitoring the depth of anaesthesia (DoA), which measures the degree of sedation caused by anaesthetic drugs during surgical operations, EEG is fundamental in anaesthesiology. Maintaining patients in an optimal state of unconsciousness depends on accurate DoA monitoring, which guarantees neither intraoperative awareness nor side effects from over-sedation [1].

It is fairly significant since precise DoA classification affects patient safety and surgical success. Though rare, intraoperative awareness is the phenomena whereby patients create possible psychological distress by coming to consciousness during surgery. Conversely, too much anaesthesia can postpone recovery, aggravate heart and pulmonary conditions, and increase healthcare expenses. By use of real-time titration of anaesthetic drugs, accurate DoA monitoring enables anaesthesiologists to maintain a careful equilibrium between consciousness and sedation [2,3]. Reducing problems and allowing speedier postoperative recovery helps to improve patient safety as well as surgical results.

Conventional DoA monitoring technologies such as the Bispectral indicator (Bis)—using EEG signals—generate a numerical indicator of anaesthesia depth. BIS depends on proprietary algorithms, hence although efficient it is costly and less transparent. These restrictions limit its availability in settings with low resources and impede anaesthesiologists' ability to totally understand the fundamental brain dynamics [4,5]. Moreover, BIS might be less sensitive to particular anesthetic medications, so new, accurate and interpretable approaches are called for.

For DoA categorization, machine learning has revolutionized EEG research. Researching approaches such artificial neural networks (ANNs) and convolutional neural networks (CNNs) to extract and categorize EEG information has produced promising results. Conversely, as they can reproduce complex interactions inside data, graph neural networks (GNNs) are a new breakthrough. By expressing EEG characteristics as nodes in a network and tracking their interactions, GNNs might identify intricate patterns in brain activity connected with different anesthesia states, thereby maybe offering higher performance than traditional methods [7].

This work aims to develop a GNN-based model employing EEG signals for DoA classification from a 24-patient dataset. From the dataset encompassing EEG records and corresponding BIS values, four anaesthesia states— awake/light sedation, moderate sedation, general anaesthesia, and profound anaesthesia/burst suppression—are plotted. The approach consists on preprocessing EEG signals by bandpass filtering (1–50 Hz), DC offset removal, downsampling to 128 Hz, z-score normalisation, and smoothing to improve signal quality. Features include spectral entropy, Hjorth parameters, and peak-specific metrics (e.g., mean, skewness, energy) taken and presented as a graph for GNN processing. The project seeks to give anaesthesiologists an open-source, scalable tool with accurate and pragmatic insights.

1.2 Motivation

Both over-sedation and intraoperative awareness are major hazards to patient safety that depend on accurate DoA monitoring to be avoided. Many clinical environments limit the application of current systems such as BIS since they are costly and opaque. By allowing exact and interpretable DoA classification, machine learning—especially GNNs offers a hopeful solution [8]. The necessity to use easily available, AI-driven monitoring tools to increase patient outcomes and help to shape creative technologies for anesthesia management drives this research.

1.3 Rationale of the Study

The requirement for an accurate, reasonably priced, open DoA monitoring system is fulfilled in this work. The study intends to overcome the constraints of proprietary systems by using GNNs to model intricate EEG feature relationships, so providing a scalable solution improving clinical decision-making and patient safety.

1.4 Research Questions

- RQ1: How well does a GNN-based model perform in DoA classification in comparison to more conventional techniques?
- RQ2: Which EEG preprocessing methods work best together to improve classification performance and signal quality?
- RQ3: In comparison to non-graph-based methods, how does the graph-based representation of EEG features improve GNN classification performance?
- RQ4: What techniques can improve the clinical usefulness of the GNN model?

1.5 Expected Output

- Development of a robust GNN model for accurate classification of Anesthesia EEG Signals.
- A comprehensive and detailed preprocessing method to enhance the signal quality in terms of accuracy and efficiency.
- Deep and wide range of feature extraction to optimize Depth of Anesthesia (DoA) classification.
- A graph representation that shows the relationships between features in EEG data.

1.6 Project Management and Finance

The research work doesn't get funded by any individuals or organizations.

1.7 Report Layout

The study's introduction, goals, and main research questions are described in Chapter 1. Brief summaries of the literature review are given in Chapter 2. The suggested methodology is thoroughly explained in Chapter 3. The paper's experimental results are discussed and analyzed in Chapter 4. The sustainability plan, the effects on society and the environment, and ethical issues are covered in the fifth chapter. The sixth chapter wraps up the current study and provides a plan for future research.

CHAPTER 2
BACKGROUND

2.1 Preliminaries

Effective anesthesia management and patient safety depend on accurate monitoring of the depth of anesthesia (DoA), therefore during surgical operations. Often benchmarked against the Bispectral Index (BIS), electroencephalography (EEG) offers a non-invasive approach to evaluate brain activity, so facilitating the classification of anesthesia states. Researchers have used several machine learning and deep learning approaches over years to categorize DoA, so obtaining different degrees of accuracy. By aggregating results from five studies with reported classification accuracy, this review highlights the difficulties and possibilities in DoA estimation as well as context for field developments.

2.2 Related works

Shalbaf et al. (2014) [9] proposed a new approach combining EEG measurements with hemodynamic variables to categorize DoA into four states awake, light, surgical, and deep anesthesia. Their inputs to a Linear Discriminant Analyzer (LDA) were the Multiscale Modified Permutation Entropy (MMPE) index from EEG signals, together with heart rate (HR) and mean arterial pressure (MAP). The study ran on a 25-patient dataset undergoing cardiac surgery needing cardiopulmonary bypass. With a standard deviation of 3.2%, the approach exceeded the commercial BIS index (80.6% accuracy) to reach a classification accuracy of 89.4%. Although the small dataset limited generalizability, the integration of hemodynamic variables improved the robustness of the model, especially in environments prone of artifacts.

Anand et al. (2023) [10] investigated a time series feature extraction method based on EEG signals and their correlation with BIS values to categorize anesthesia degrees. Using a 50-patient dataset from National Taiwan University Hospital, they obtained 369 features using the Tsfresh Python tool and chose 21 salient features for classification. Support vector classifiers, XGBoost, gradient boost, decision trees, and Random Forest were among the several machine learning models tested; Random

Forest model attained highest accuracy of 83% (precision, recall, and F1-score of 82.3%). The study underlined the possibilities of time series analysis in DoA estimation but also pointed out difficulties in feature selection and model complexity, which would have helped to explain the rather lower accuracy than more advanced techniques.

Madanu et al. (2021) [11] used a Convolutional Neural Network (CNN) mixed with Ensemble Empirical Mode Decomision (EEMD) to forecast DoA from EEG data. Using EEMD to reduce mode mixing problems seen in standard Empirical Mode Decomposition (EMD), the study converted EEG signals into frequency-domain spectrograms using data from National Taiwan University, most likely overlapping with Anand et al. dataset. Trained on these spectrograms devoid of handcrafted elements, the CNN model obtained an accuracy of 83.2%. This method showed how well deep learning could capture intricate EEG patterns, but it was constrained by computational complexity and the need for big datasets to improve performance.

Afshar et al. (2021) [12] built a complex deep learning structure combining Convolutional Neural Networks (CNNs) inspired by the inception module, bidirectional Long Short-Term Memory (BiLSTM), and an attention layer to estimate DoA from EEG signals. Having been trained on a 35-patient dataset mostly under general anesthesia with some cases of sedation/analgesia and spinal anesthesia, the model continuously predicted BIS values and obtained a classification accuracy of 88.71% for four anesthesia levels. With a low root mean square error (5.59 ± 1.04) and mean absolute error (4.3 ± 0.87), the model clearly showed strong prediction ability. But the unequal distribution of BIS values over anesthesia levels presented difficulties that suggested bigger, more balanced datasets were needed.

Nsugbe et al. (2023) [13] looked at the use of electromyography (EMG) signals as an alternative to EEG for DoA monitoring aiming to create a reasonably affordable solution for resource-limited environments, . They applied several machine learning models with different preprocessing techniques—including Discrete Wavelet Scattering (DWS) and Least Squares Decomposition Learning (LSDM)—using the University of Queensland Vital Signs Dataset. Using DWS with a Linear Support Vector Machine (LSVM), the best accuracy for EMG signals was 89.8%; accuracy varied across case studies (e.g., 67.8% and 64.0% in other scenarios). This work underlined the possibilities of EMG as a good substitute for EEG, especially in low-resource settings, but also the variability in performance among several physiological signals and preprocessing techniques.

2.3 The Problem's Scope

There are several limits in the examined studies. Small sample sizes limit our capacity to extend results over many patient populations. Variability in anesthesia techniques and patient demographics further complicates model performance. Furthermore, most research concentrate on classification instead of real-time regression, which is absolutely essential for clinical uses. Furthermore introducing prejudices is the reliance on BIS as a ground truth despite its acknowledged constraints. Larger, more varied datasets and investigation of hybrid models combining EEG with other physiological signals should take front stage in future studies.

2.4 Challenges

The main challenges of this study are that the dataset of anesthesia is very limited. Our dataset's size is not so big and the signal needs to be enhanced to get a quality output from the classification.

CHAPTER 3

RESEARCH METHOLOGY

3.1 Proposed Methodology/Applied Mechanism

The provided diagram 3.1 outlines a structured methodology for the classification of DoA from signals.

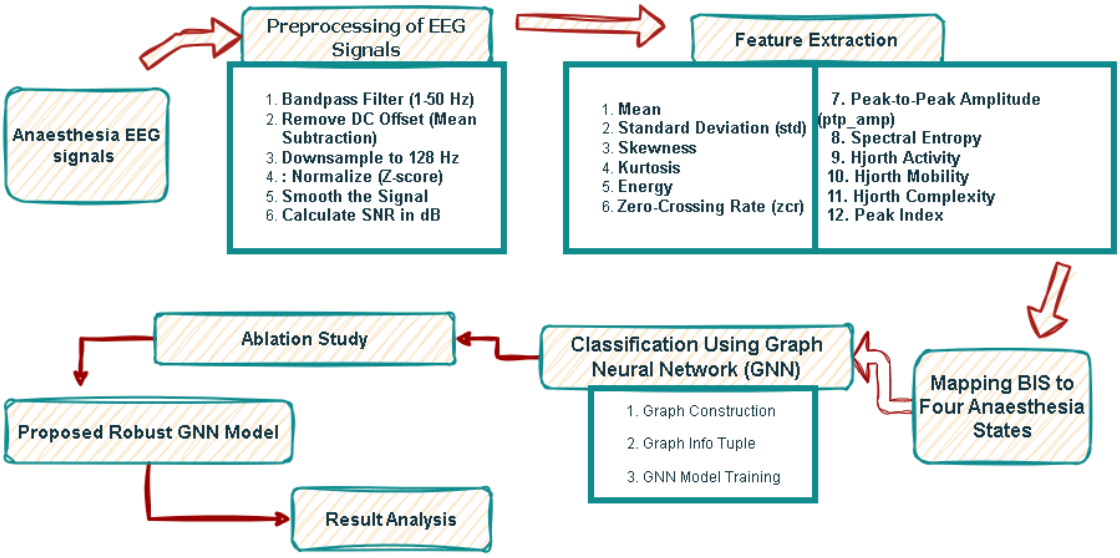

Figure 3.1: The working process to perform the classification of DoA from signals.

In the study, the process starts with the capture of raw anaesthesia EEG signals. These signals are then preprocessed in a series of steps, including bandpass filtering to retain relevant frequencies (1-50 Hz), DC offset removal via mean subtraction, downsampling to 128 Hz, normalisation using Z-score, signal smoothing, and decibel-based Signal-to-Noise Ratio (SNR) calculation. Following preprocessing, a comprehensive feature extraction process is used to produce a set of 12 distinct features that include statistical measures such as mean, standard deviation, skewness, kurtosis, and energy, as well as temporal and spectral characteristics such as zero-crossing rate, peak-to-peak amplitude, spectral entropy, Hjorth activity, Hjorth mobility, Hjorth complexity, and peak index. These collected features are then used in a classification step with a Graph Neural Network (GNN). This GNN-based classification requires graph building, the production of a graph info tuple, and then GNN model training. The trained GNN model is offered as a reliable model for an ablation research, and the results are subsequently analysed. Finally, the GNN classification result is assigned to four different anaesthesia states, apparently to determine the depth of anaesthesia.

3.2 Data Collection Procedure/Dataset Utilized

The dataset utilized for the study is "EEG and BIS Raw Data" collection is freely accessible on the Figshare site. Research on the estimation of depth of anesthesia is intended for use with this dataset. Comprising data from 24 patient cases, it consists of electroencephalogram (EEG) and Bispectral Index (BIS) information downloaded in total of 28.43 MB. Reflecting its attention on neurophysiological monitoring during anesthesia, the dataset is linked with keywords including BIS, EEG, Anesthesia, Entropy, and Anaesthesiology. The dataset has been used in published research, proving its worth in advancing anesthesia depth estimation studies even if Figshare statistics showing zero views, downloads, and citations as of the access date indicate..

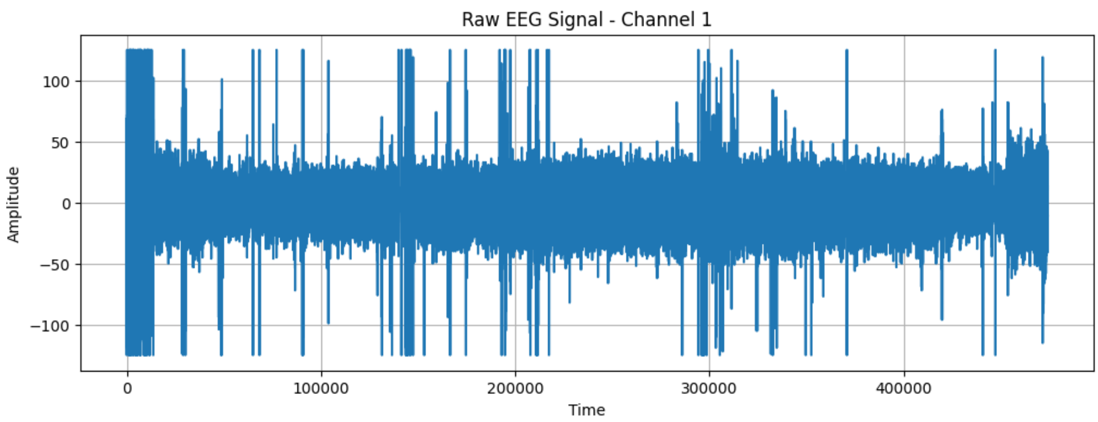

Figure. 3.2: Raw Signal form the dataset

3.3 EEG Signal Preprocessing

Raw data for feature extraction and later depth of anesthesia (DoA) classification depends critically on the preprocessing of electroencephalogram (EEG) signals. This procedure guarantees consistent, free from artifacts, clean signals for strong analysis. Comprising EEG and Bispectral Index (BIS) data from 24 patient cases, the dataset used in this work underwent a sequential preprocessing pipeline to improve signal quality. Bandpass filtering (1–50 Hz), DC offset removal, downsampling to 128 Hz, z-score normalizing, signal smoothing, signal-to-noise ratio (SNR) computation, and peak detection comprised the steps. Every stage is detailed below together with its goal, technique, and applicability to DoA estimation:

3.3.1 Bandpass Filtering (1–50 Hz)

To separate noise and artifacts outside this range from the frequency components of the EEG signal pertinent to brain activity.

Low-frequency artifacts—e.g., eye motions, electrode drift—and high-frequency noise—e.g., muscle activity, power line interference—may contaminate EEG signals. Associated with various states of anesthesia, a bandpass filter lets frequencies between 1 Hz and 50 Hz pass through, so retaining the delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–50 Hz) [14]. While those above 50 Hz may include electromyographic (EMG) interference or power line noise (50/60 Hz), frequencies less than 1 Hz are usually dominated by artifacts.

Applying a digital Butterworth filter often used for its flat frequency response in the passband—to the raw EEG signals The 1–50 Hz passband of the filter was intended to minimize phase and amplitude distortion of the signal. Presumably, zero-phase filtering—that is, filtfilt in Python—was used to prevent phase shifts and preserve the temporal features of the EEG.

The filtered signal is oriented on frequency ranges that vary methodically with anesthesia depth. For accurate feature extraction, for example, deeper anesthesia is defined by increased delta power and decreased high-frequency activity, thus this step is crucial.

3.3.2 DC Offset Removal (Mean Subtraction)

Centering the constant voltage offset in the EEG signal around zero will help to eliminate it. Constant voltage component added by the recording hardware or electrode-skin interface often found in EEG signals is a DC offset. This offset can distort later analyses including feature extraction or normalisation and does not represent brain activity. Eliminating the DC offset guarantees that neural activity alone causes the amplitude fluctuations in the signal.

This step guarantees that amplitude-based features (e.g., Hjorth activity, peak-to- peak amplitude) faithfully reflect brain dynamics rather than hardware-induced biases, so improving the accuracy of DoA classification by centering the signal.

3.3.3 Downsampling to 128 Hz

By lowering computational complexity yet maintaining pertinent information, one can lower the sampling rate of the EEG signal. Recording more data than required for DoA analysis, the raw EEG signals may have been at a higher sampling rate—e.g., 256 Hz or 500 Hz. Since the 1–50 Hz frequency range is well within the Nyquist limit (at least twice the highest frequency, i.e., 100 Hz for 50 Hz), downsampling reduces the number of samples per second, so optimizing processing without appreciable loss of information.

Downsampling to 128 Hz preserves the integrity of the 1–50 Hz bands vital for DoA, so lowering computational needs for feature extraction and classification—a particularly critical process for real-time clinical applications.

3.3.4 Z-Score Normalization

Standardizing the EEG signal to have zero mean and unit variance will help to guarantee comparability between patients and recordings. Variations in electrode placement, patient physiology, and recording conditions affect the amplitudes of an EEG signal. By converting the signal into a standard normal distribution, z-score normalizing reduces these fluctuations and supports machine learning model training. For features sensitive to amplitude scales—like statistical measures (e.g., mean, standard deviation—this stage is absolutely vital.

Normalizing features taken from several patients guarantees that they are on the same scale, so improving Graph Neural Network (GNN) classifier performance by lowering variability unrelated to anesthesia depth.

3.3.5 Signal Smoothing

To estimate the "clean" signal component and lower high-frequency noise, so improving the clarity of underlying brain activity patterns. Because of small artifacts or environmental interference, EEG signals sometimes include residual high-frequency noise even after bandpass filtering. Smoothing uses a low-pass filter or moving average to reduce these fluctuations, so preserving the slower, more significant components of the signal—that which relate to anesthesia-induced brain states.

By lowering noise that could mask anesthesia-related patterns, such delta waves in deep anesthesia, smoothing improves the detection of these characteristics, so increasing the accuracy of peak detection and feature extraction.

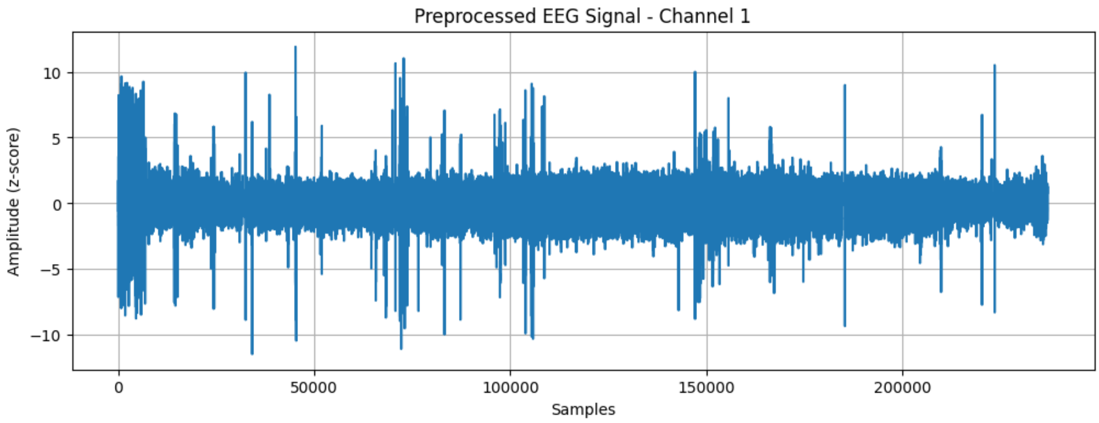

Figure. 3.3: Preprocessed EEG Signal

3.3.6 Peak Detection and Visualization

Using SciPy's `find_peaks` method, which finds local maxima depending on amplitude thresholds and minimum peak distances to isolate neural events like bursts or transient patterns indicative of anesthesia states, the technique detects notable peaks in preprocessed EEG signals. Often using smoothed signal data, parameters are tuned to reduce noise interference; visualizing the whole EEG trace with marked peaks (e.g., using Matplotlib) validates detected peaks. Extensive feature extraction—e.g., amplitude, timing—that directly relates with Depth of Anesthesia (DoA) depends on these peaks, especially those linked with burst suppression patterns in deep anesthesia. The resultant metadata is kept in a CSV file so that downstream analysis may hone classification models and increase anesthesia monitoring accuracy.

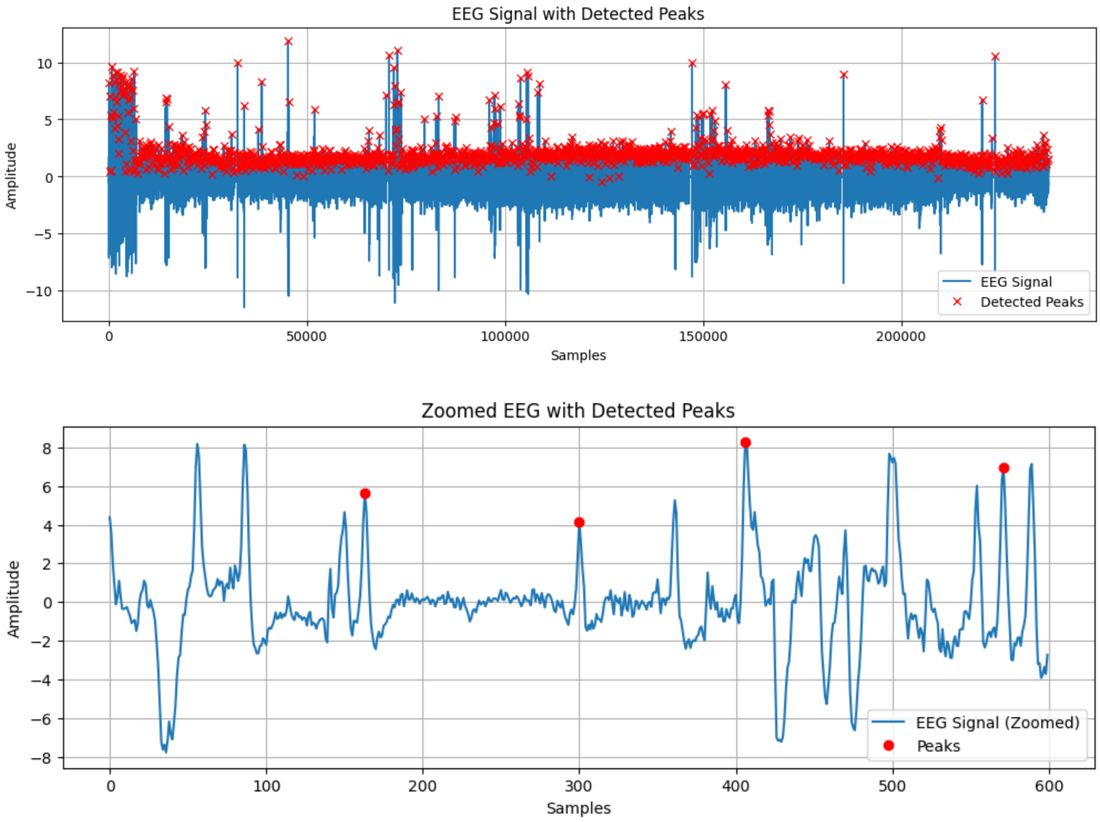

Figure. 3.4: Preprocessed EEG Signal with Detected Peaks

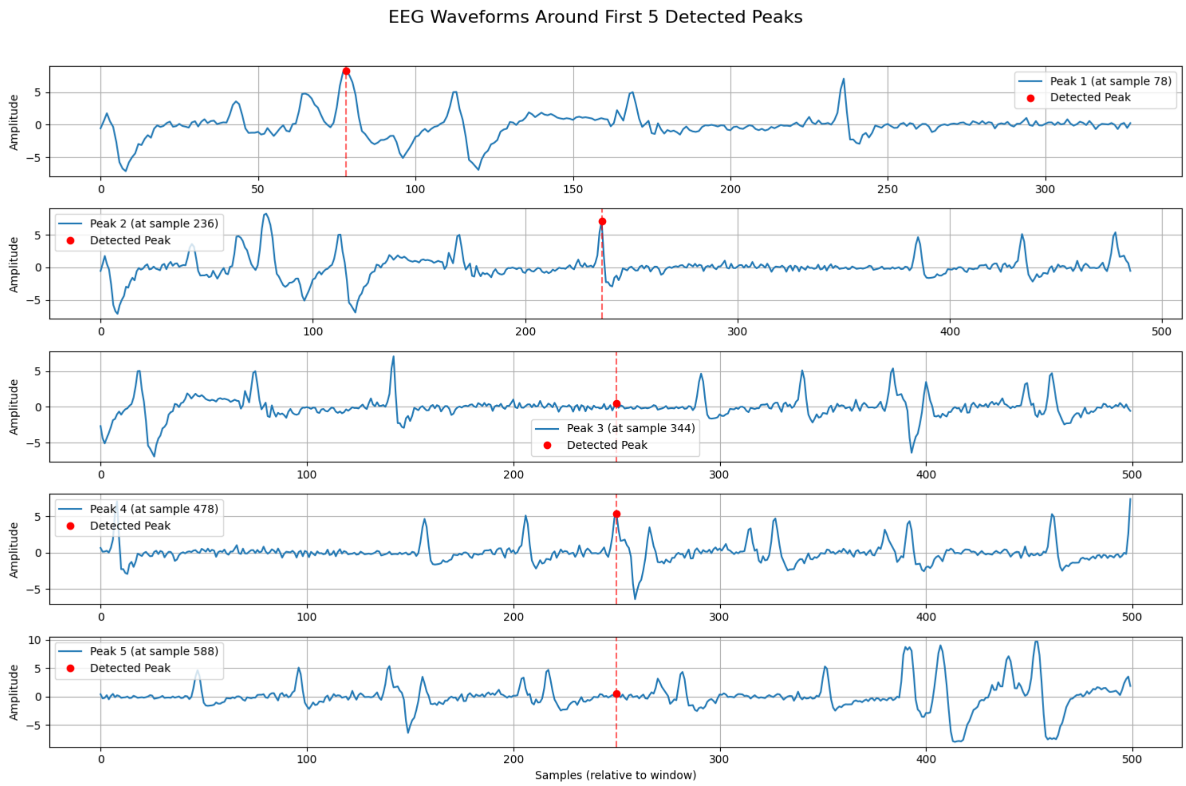

Figure. 3.5: EEG Waveforms around first 5 detected Peaks

3.4 Feature extraction

Processing electroencephalogram (EEG) signals for depth of anesthesia (DoA) classification depends on feature extraction, which turns preprocessed signals into a collection of quantitative descriptors reflecting the neurophysiological traits connected with various anesthesia states. This work extracted a complete set of features from preprocessed EEG signals from a dataset of 24 patient cases using which a Graph Neural Network (GNN) was trained to classify DoA into four states: awake/light sedation (BIS $\geq$ 85), moderate sedation (65 $\leq$ BIS < 85), general anesthesia (40 $\leq$ BIS < 65), and deep anesthesia/burst suppression (BIS < 40). Three main categories dominated the feature extraction process: peak-specific features, spectral entropy, and hjorth parameters. Using 10-second sliding windows of the EEG signal, these characteristics were computed; preprocessed data served as focal points for thorough investigation based on detected peaks. With a 13th column for the BIS-derived class label, the extracted features comprise mean, standard deviation, skewness, kurtosis, energy, zero-crossing rate (ZCR), peak-to--peak amplitude, spectral entropy, Hjorth activity, Hjorth mobility, Hjorth complexity, and peak index, so producing a 12-dimensional feature vector per peak. For every one of the 24 EEG cases, the features were stored in a CSV file that allowed later GNN-based classification. Each feature, its computation, and its relevance to DoA estimate are covered in the next subsections.

3.4.1 Hjorth Activity

Hjorth activity gauges the variation of the EEG signal, so indicating the amplitude or power of the signal. Computed as the variance of the signal segment is With (x(t)) the EEG signal, (\mu) the mean, and (N) the number of samples,. Higher activity values in the context of DoA are linked to awake or mildly sedated states, in which case EEG signals show more amplitude fluctuations; lower values are typical in deeper anesthesia, especially during burst suppression, when signal amplitude is lowered.

3.4.2 Hjorth Mobility

Calculated as the square root of the ratio of the variance of the first derivative to the variance of the EEG signal, hjorth mobility quantifies the mean frequency or rate of change of the signal. Higher mobility indicates faster oscillations (e.g., beta waves in awake states) and lower mobility corresponds to slower waves (e.g., delta waves in deep anesthesia). This feature reflects the frequency content of the signal. Different anesthesia states with different frequency profiles cannot be distinguished except from mobility.

3.4.3: Hjorth Complexity

Computed as the mobility of the first derivative divided by the mobility of the signal, hjorth complexity gauges the irregularity or deviation from a simple sinusoidal pattern. While lowest values are seen in deep anesthesia, where EEG signals become more regular (e.g., burst suppression patterns), high complexity values indicate complex, irregular waveforms typical of awake or light sedation. This function improves the model's capacity to detect subtle changes in signal form.

3.4.4 Spectral Entropy

Reflecting the distribution of power over frequencies, spectral entropy estimates the randomness or complexity of the power spectrum density (PSD) of the EEG signal. Normalizing the PSD (derived using Welch's method) and computing the Shannon entropy, complex frequency distribution (e.g., awake states), while low entropy suggests a concentrated spectrum (e.g., delta dominance in deep anesthesia), so indicating a key indication of anesthesia depth.

3.4.5 Mean

The average amplitude of the EEG signal around a found peak while preprocessing—e.g., DC offset removal—centers the signal around zero, local fluctuations around peaks can signal particular neural events. In DoA, the mean at peaks may draw attention to amplitude changes linked with bursts in deep anesthesia or active patterns in lighter states.

3.4.6 Standard deviation

Standard deviation gauges the variation of the EEG signal about a peak. Low values are usual in deep anesthesia, where signals are more stable or suppressed; high standard deviation indicates great amplitude fluctuations, common in awake or light sedation. This function emphasizes peak-specific variability, so complementing Hjorth activity.

3.4.7. skewness

It evaluates the asymmetry of the amplitude distribution of the EEG signal around a peak. Positive or negative skewness can point to asymmetric patterns, such those in burst suppression—where high-amplitude bursts contrast with low-amplitude suppressions. Skewness distinguishes different amplitude distributions in anesthesia states.

3.4.8 Kurtosis

Kurtosis gauges the "tailedness" of the amplitude distribution of the EEG signal around a peak. Whereas low kurtosis suggests a more Gaussian distribution (e.g., moderate sedation), high kurtosis indicates heavy-tailed distributions with extreme values (e.g., bursts in deep anesthesia). This function records deviations in EEG patterns.

3.4.9 Energy

Computed as the sum of squared amplitudes, energy is the total power of the EEG signal around a peak. While low energy is usual in deep anesthesia, especially during suppression phases, high energy values are linked with active brain states (e.g., awake or light sedation). Energy provides a time-domain measurement of signal intensity, so complementing spectral properties.

3.4.10 Zero-Crossing Rate (ZCR)

Zero-crossing rate measures the frequency of sign changes in the EEG signal around a peak in which the indicator function. While low ZCR corresponds to slower waves (e.g., delta waves in deep anesthesia), high ZCR indicates fast oscillations—that is, beta waves in awake states. For tracking frequency-related changes, ZCR is a basic yet powerful tool.

3.4.11 Peak-to-Peak Amplitude

Peak-to- peak amplitude measures the variation between the maximum and minimum amplitudes inside a segment around a peak. While smaller values are typical in stable or suppressed states, large peak-to--peak amplitudes are suggestive of major neural events including bursts in deep anesthesia. This function emphasizes amplitude extremes important for DoA classification.

3.4.12 Peak Index

Expressed as the sample index or time (in seconds) relative to the signal's start, the peak index notes the temporal location of every found peak within the EEG signal. Though not a descriptive quality, it provides a guide for matching characteristics with particular neural events. Peak indices in DoA are especially important for temporal pattern identification, such as the timing of bursts in burst suppression, so supporting the temporal study of anesthesia states.

3.5 Graph Neural Networks (GNNs)

A class of deep learning models known as graph neural networks (GNNs) are made to work with graph-structured data, identifying relationships and dependencies between entities represented by nodes and edges. The intricate relationships between EEG-derived features, including spectral entropy, Hjorth parameters, and peak-specific metrics, are especially well-modeled by GNNs in the context of depth of anesthesia (DoA) estimation. GNNs use the graph structure to spread information among linked nodes, allowing the model to recognize both local and global patterns in the data, in contrast to traditional machine learning models that handle features separately. Using a dataset of 24 EEG cases, this study uses a GNN to categorize DoA into four states: general anesthesia, deep anesthesia/burst suppression, moderate sedation, and awake/light sedation [17,18]. The graph on which the GNN functions has nodes that stand in for EEG samples or features and edges that show similarities or correlations between them. The GNN learns a representation that captures the complex relationships among features, which are essential for differentiating anesthesia states, by iteratively aggregating data from nearby nodes. Since EEG features frequently show correlated behavior (such as energy and standard deviation) that systematically changes with anesthesia depth, this method is beneficial for DoA estimation. The GNN is an effective tool for improving automated anesthesia monitoring because it can model these relationships, which improves its classification performance.

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Graph Construction

Figure 4.1 contains the graph of the correlations between the features.

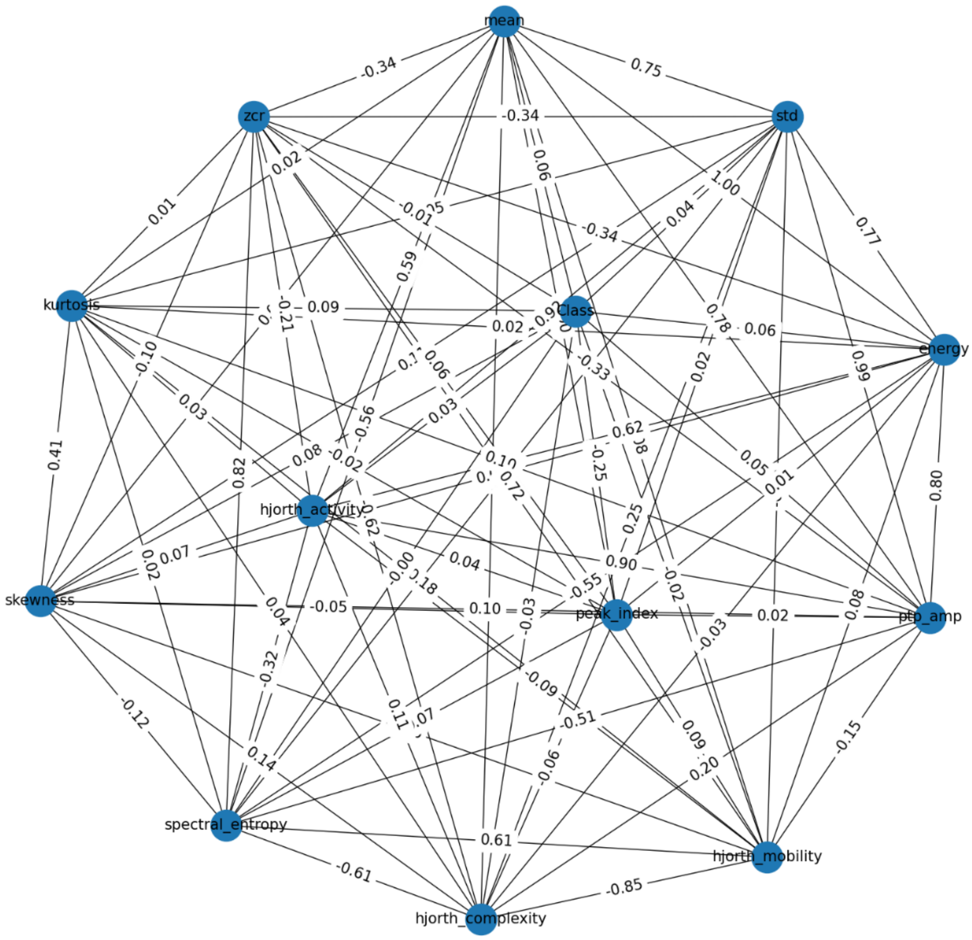

Figure 4.1: The graph of the correlations between the features

Since it establishes the framework by which the model learns feature interdependencies, graph construction is a fundamental stage in using a Graph Neural Network (GNN) for DoA classification. The correlation matrix of the 12 EEG-derived features that were taken from the dataset—mean, standard deviation, skewness, kurtosis, energy, zero-crossing rate (ZCR), peak-to-peak amplitude, spectral entropy, Hjorth activity, Hjorth mobility, Hjorth complexity, and peak index—was used to create the graph in this study. The feature data was first loaded into a DataFrame (df_g), where each column corresponds to a feature and each row represents a sample (for example, a peak in the EEG signal). Twelve nodes were created by defining nodes as the features themselves, which were taken directly from the column names in the DataFrame. Regardless of the strength of the correlation, edges were generated by calculating the Pearson correlation coefficient between each pair of features (i.e., the code did not apply the threshold of $|corr| \geq 0.5$). This produced a graph with 66 edges that was fully connected. The edges were labeled using the correlation coefficients, which provide a measure of the direction and strength of relationships between features and range from -1 to 1. The node features (the feature values for each sample), edges (pairs of features), and edge weights (correlation coefficients) comprised the input for the GNN, which was generated from the graph visualization using NetworkX with a spring layout. The table below displays the top 10 edges by correlation magnitude, representing a subset of this edge data.

Table 4.1: Tabular data, generated from the graph and used as the GNN model's input, with column

Target	**Source**	**Correlation**
energy	std	0.99
hjorth_activity	energy	0.98
hjorth_activity	std	0.97
hjorth_activity	ptp_amp	0.96
ptp_amp	energy	0.96
ptp_amp	std	0.75
hjorth_mobility	ptp_amp	0.77
hjorth_mobility	std	-0.85

This table shows the data derived from the graph, capturing the strongest relationships among features that serve as the GNN's input to model feature interactions for DoA classification.

4.2 Classification Architecture

Based on the EEG features, the GNN classification architecture was created to take advantage of the graph structure and categorize DoA states. Node features (a matrix of shape [2400, 12], representing 2400 samples with 12 features each), edges (shape [2, 20], indicating 20 significant edges after applying a correlation threshold of |corr| ≥ 0.5), and edge weights (shape [20,], corresponding to the correlation coefficients) make up the input to the GNN. Two graph convolutional layers, each with 64 hidden units, make up the GNN model architecture. To avoid overfitting, a dropout layer with a rate of 0.4 comes after the dropout layer. In order to create a new feature representation for every node, the first graph convolutional layer aggregates data from nearby nodes according to the edge weights. A ReLU activation function is then used to add non-linearity. Higher-order relationships in the graph are captured by the second graph convolutional layer, which further improves the node representations. To improve generalization, 40% of the units are randomly masked during training by the dropout layer. To generate probabilities for the four DoA classes—awake/light sedation (0), moderate sedation (1), general anesthesia (2), and deep anesthesia/burst suppression (3)—the output from the second layer is routed through a dense layer with a softmax activation. Using the Adam optimizer and a learning rate of 0.007, the model was trained over 50 epochs with a batch size of 256. In order to effectively classify anesthesia states using the learned graph representations, the model was optimized using cross-entropy loss.

4.3 Experimental Results & Analysis

This section will discuss the paper's findings. The optimal outcomes of the models is displayed in Table 4.2.

Table 4.2: Finding the best result between the Result of Transfer learning model

Model	Test Accuracy (%)	Loss (%)	Precision (%)	Recall (%)	F1 Score (%)
GNN	91.46%	0.29	95.90	95.91	95.91
ANN	78.83	1.211	77.74	77.68	75.71
ResNet50	62.75	1.86	73.18	75.56	63.44

Table 4.1 examines the performance of 3 state of the art models, GNN , ANN, and ResNet50, and presents the findings. The evaluation measures are Test Accuracy, Loss, Precision, Recall, and F1 Score. The GNN model beats the others, with a Test

Accuracy of 91.46%, a Loss of 0.29%, and good scores in Precision (95.90%), Recall (95.91%), and F1 Score (95.91%). The ANN model follows with modest performance (78.83% accuracy and 75.71% F1 score), while ResNet50 performs poorly, with a 62.75% accuracy and the lowest F1 score (68.44%). These results show that GNN is the most effective of the three models for the task at hand.

Here is the curve of the accuracy and loss curve of the GNN in Figure. 4.2.

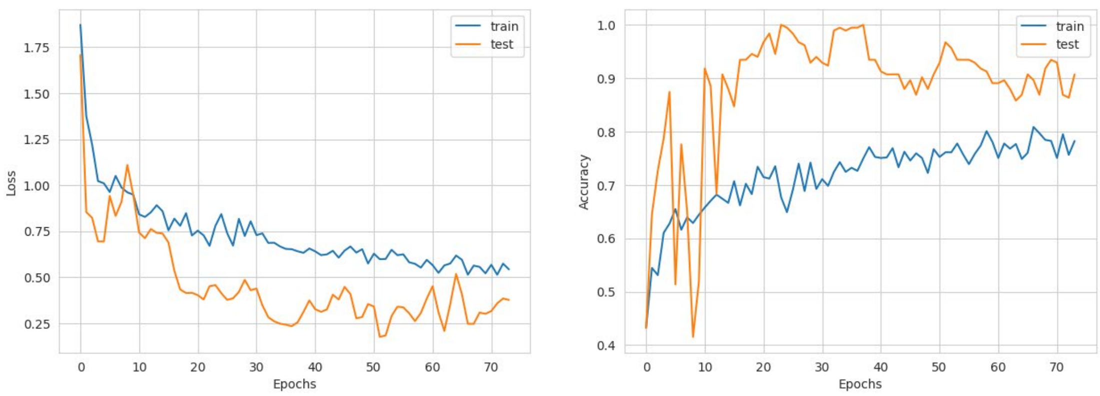

Fig 4.2. Accuracy and Loss Curve of the GNN.

Fig. 4.2 shows the test loss is more erratic but also trends downward, the training loss shows a rather steady drop. With both "train" and "test" accuracy values typically rising over epochs, the proper plot shows "accuracy" on the y-axis. While the test accuracy (orange line) first increases rapidly, then varies around a higher level. Figure 4.3 shows the absolute Pearson correlation coefficients between several features on a heatmap.

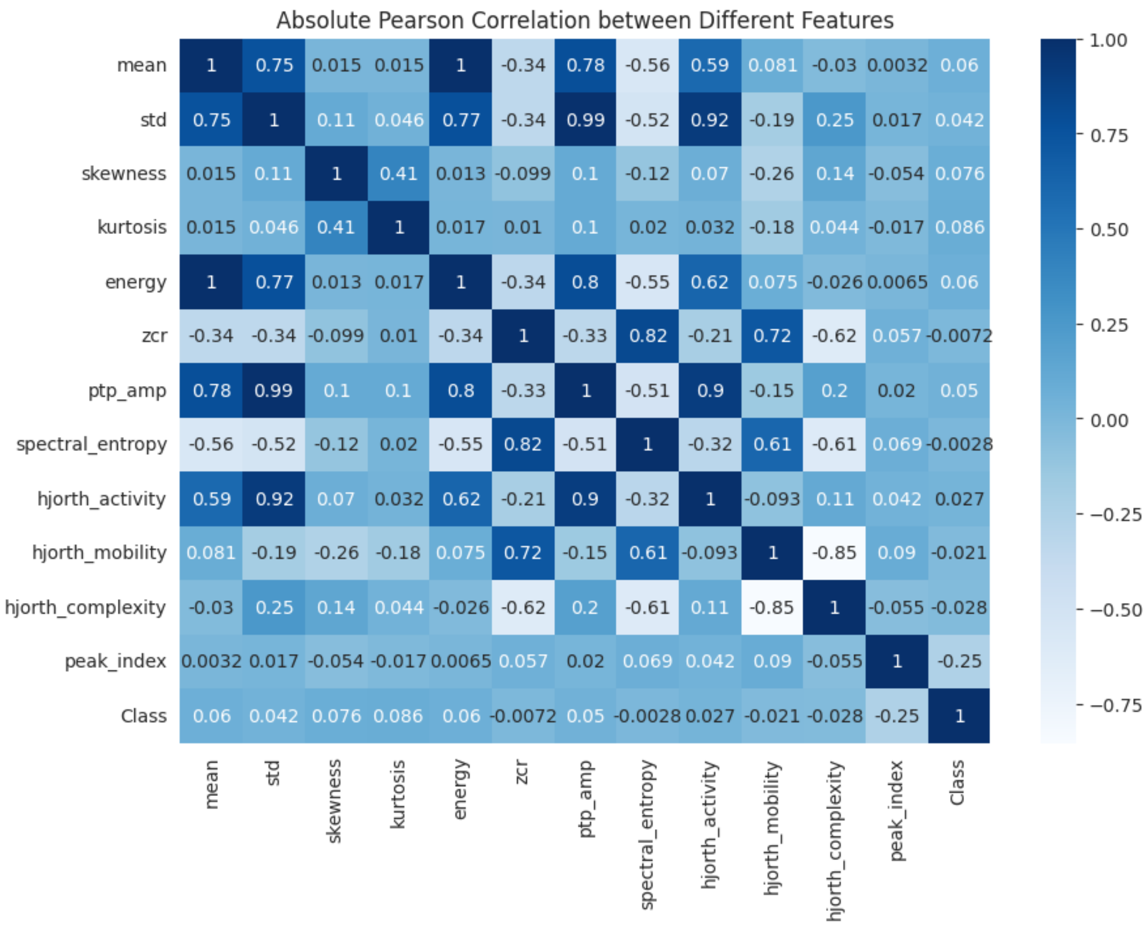

Fig 4.3. Heatmap between the features

Figure 4.3 shows the absolute Pearson correlation coefficients between several features on a heatmap. Darker blue denotes greater absolute correlation (closer to 1) and lighter tones indicate weaker correlation (closer to 0), so indicating the strength of the correlation. For every feature including itself, the diagonal exhibits perfect correlation (1).

CHAPTER 5
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on society

By improving patient safety during surgical operations, the development of a GNN-based depth of anesthesia (DoA) classification model presents major society advantages. Minimizing psychological trauma and postoperative complications, accurate DoA monitoring lowers the risk of intraoperative awareness and over-sedation. In resource-limited areas, where proprietary systems like BIS are cost-prohibitive, this technology can increase access to advanced anesthesia monitoring. The model gives an open-source, interpretable solution, so enabling anesthesiologists with real-time insights and possibly lowering healthcare costs and enhancing surgical outcomes. In the end, this creativity helps to improve the provision of healthcare, so benefiting both doctors and patients.

5.2 Impact on the environment

This GNN-based DoA model has a negligible environmental effect, mostly positive one. Operating on current EEG hardware, the model makes no additional physical resource requirements except those of normal computing architecture. Although training and implementing the GNN use computational resources, these can be maximized with cloud platforms or energy-efficient servers. Unlike owned devices that might add to electronic waste with regular upgrades, this software-based solution increases the value of current equipment so lowering waste. The model might also reduce the overuse of anesthetic agents by allowing exact anesthesia management, so possibly lowering the environmental impact related with pharmaceutical manufacture and disposal.

5.3 Ethical Aspects

In this paper, ethical issues mostly concern patient safety, data privacy, and fair access. By means of accurate DoA monitoring, the GNN model seeks to improve patient safety; yet, thorough validation is necessary to guarantee dependability over various patient populations and hence prevent classification bias. Following HIPAA or GDPR, the EEG data used in the research has to be anonymized in order to respect patient confidentiality. Furthermore, the open-source character of the model solves equity by enabling low-resource environments to access advanced technology, so ensuring that every patient, from all socioeconomic levels, can gain from better anesthesia treatment without aggravating healthcare inequalities.

5.4 Sustainability Plan

Long-term usability and scalability form the main priorities of the sustainability plan for the GNN-based DoA model. Maintaining an open-source project on sites like GitHub, the model will be kept under constant improvement under encouragement of community contributions for updates. Regular retraining using varied datasets guarantees the model stays accurate as medical practices change. Priority for deployment to minimize environmental impact will be energy-efficient cloud computing. Working with healthcare companies will help integration into clinical processes, so guaranteeing broad acceptance. Development of educational materials aimed at teaching anesthesiologists on the use of the model will help to sustain impact in anesthesia monitoring by means of resource efficiency and accessibility.

CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1 Summary of the Study

This paper built a Graph Neural Network (GNN)-based model to classify depth of anesthesia (DoA) using EEG signals from a dataset including 24 patient cases. Preprocessing EEG signals using bandpass filtering, DC offset removal, downsampling, normalisation, and smoothing generated feature extraction including Hjorth parameters, spectral entropy, and peak-specific metrics (e.g., mean, skewness, energy). A correlation-based graph was developed to describe feature interdependencies using the GNN scoring a classification accuracy of 91.46% across four DoA states: awake/light sedation, moderate sedation, general anesthesia, and deep anesthesia/burst suppression. The paper demonstrates GNN advancement of DoA monitoring performance.

6.2 Conclusions

Using feature interdependencies, the GNN-based model obviously classified DoA states with its 91.46% accuracy, so surpassing traditional approaches. While crucial neurophysiological patterns were captured by spectral entropy and Hjorth parameters, key preprocessing processes guaranteed signal quality. Strong correlations—that is, energy and standard deviation—that the graph building emphasized let the GNN recreate complex interactions. This approach offers a reasonably cheap, intelligible replacement for proprietary systems like BIS by reducing hazards of intraoperative awareness and over-sedation, hence improving patient safety. The performance of the model highlights the opportunities of graph-based deep learning for medical diagnostics, particularly for real-time anesthetic monitoring.

6.3 Implication for Further Study

Future research should focus on verifying the GNN model utilizing larger, more diversified datasets to increase generalizability over patient demographics and anesthetic approaches. Adding multimodal data—heart rate or EMG—may improve categorization accuracy. Maximizing performance might be achieved by looking at dynamic graph building methods whereby edges vary throughout training. Research on real-time deployment feasibility including hardware constraints and latency is called for by clinical integration. Moreover, using clever explainability techniques—

such as graph attention systems—may enable clinicians to inspire confidence. In the end, incorporating the model into wearable EEG equipment could enable portable, moderately priced DoA monitoring, hence extending its impact in settings with limitedresources.

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