EEG-based Emotion Recognition using Spectral GNN on DEAP Dataset

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Declaration

I hereby declare that this report, except where specific references are made to the works of others, is original and has not been submitted elsewhere for any degree or qualification. The work presented herein is my own, conducted independently unless explicitly stated in the text or acknowledgments. The dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements

P.Pushyamithra
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Abstract

This report presents the use of electroencephalography (EEG) for emotion recognition. We explore challenges associated with EEG data, including signal quality, limited spatial resolution, and non-linearity. The study emphasizes a framework for EEG-based emotion recognition using Spectral Graph Neural Networks (GNNs) applied to the DEAP dataset. The methodology encompasses preprocessing EEG data into 2-second segments, implementing a spectral GNN with Graph Fourier Transform (GFT) and Chebyshev convolutions, exploring pooling mechanisms (Top-K, SAG, mean), generating enhanced graph embeddings, and computing subject-wise and overall accuracies for valence and arousal classification. Key innovations include segmenting 60-second trials into 30 segments for fine-grained analysis, leveraging spectral graph theory, and optimizing GNNs with residual connections and weighted Phase Locking Value (PLV). Results indicate overall accuracies of 63.53% for valence and 59.49% for arousal, with subject-wise accuracies spanning a wide range. Visualizations, including connectivity graphs, training curves, confusion matrices, and t-SNE embeddings, provide comprehensive insights into model performance and emotional patterns. This work advances EEG emotion recognition by integrating spectral analysis with a multi-stage GNN optimization, offering a robust foundation for future research in affective computing.

Keywords: EEG, Emotion Recognition, Spectral Graph Neural Networks, Graph Fourier Transform, Chebyshev Convolutions, DEAP Dataset

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Chapter 1

Introduction

There are roughly about 86 billion neurons, and they are the most fundamental building blocks of the nervous system. These neurons are connected from their two ends namely the dendrites and the axon. The neurons communicate with each other via a combination of chemical and electrical signals. Whenever thousands of neurons are activated or fired synchronously, they generate electrical currents and thus magnetic fields, which are strong enough to propagate through tissues, bones, and skulls. These signals are a consequence of the action potentials which are generated when human brain detects any of the activity. It generates a few ions which cause the action potential to occur. So this potential can be measured using electrodes, placed either superficially on skull, or on brain or inserting them carefully inside the brain. By analyzing these brain wave patterns, Brain Computer Interface brings a new revolution of controlling connected devices just by a human's thoughts, without muscle control. A Brain Computer Interface (BCI) is fundamentally a computer-based system that analyzes the acquired brain signals and translates them into some kind of commands that can be relayed to an output which may enhance, replace, supplement, restore or improve human function

1.1 Background and Motivation

Emotion recognition is the process of recognize human emotions based from Neural Signals, Facial Expressions, Voice Analysis, etc. Among all methods, brain signals speak much about the Emotions as the emotions are caused due to neurophysiological changes. The most common ways to capture brain signals are electroencephalography (EEG), Electrocorticography (ECoG), Intracranial Electrodes, etc. Of these EEG is the most 2 common way used to recognize human emotions as it is non-invasiveness, high temporal resolution, low cost, portability, and ease to use.

Electroencephalography (EEG) is a non-invasive technique that captures electrical activity in the brain, making it a valuable tool for studying cognitive processes, including emotion recognition. It is a dynamic and versatile tool for recording electrical activity in the brain. In the domain of affective computing, EEG is employed to capture the fleeting nuances of human emotion. Traditional EEG analysis focuses primarily on signal waveforms, power spectral densities, and time-frequency decompositions. However, these methods often neglect the complex interplay between distributed brain regions that underlie emotional processing.

Modern neuroscience suggests that emotions are not localized but rather emerge from the networked interactions among various brain regions. With the rise of graph-based representations, each EEG electrode can be considered as a node and the connectivity (e.g., phase synchronization) between electrodes as the edges. This conversion from a “flat” signal to a network perspective opens up innovative methods for feature extraction and pattern recognition. Emotions, as complex psychophysiological states, influence brain connectivity and can be decoded from EEG signals for applications in Brain-Computer Interfaces (BCIs), mental health monitoring, and affective computing.

The DEAP dataset, comprising EEG recordings from 32 subjects across 40 trials of 60-second duration, is a widely used benchmark for emotion recognition, providing valence and arousal labels.

The motivation for this research emerges from the desire to harness these interconnected relationships by applying spectral analysis techniques to the graph representation of EEG data. By leveraging the Graph Fourier Transform (GFT), the network signals can be interpreted in the frequency domain, revealing hidden patterns that are otherwise obscured in the time domain. Furthermore, Chebyshev convolutions offer an efficient means of filtering and learning in the spectral domain, bridging theory and practice in the construction of a Graph Neural Network (GNN) tailored for emotion recognition.

1.2 Research Objectives

The central objectives of this study include:

- **Refined Data Handling:** To rigorously preprocess raw EEG data, segment it into 2-second time windows to capture fine-grained temporal variations, and extract well-defined frequency-domain features using power spectral density (PSD) analysis.

- **Spectral Graph Construction:** To construct PLV-based connectivity graphs that capture the degree of synchronization between different brain regions.

- **Innovative GNN Architecture:** To develop a spectral GNN that integrates both Graph Fourier Transform and Chebyshev convolution layers, thereby harnessing the spectral characteristics of the EEG connectivity graph.

- **Pooling and Embedding Analysis:** To compare multiple graph pooling strategies—Top-K, Self-Attention Graph (SAG), and mean pooling—to determine how these aggregation methods influence the final graph-level representations. Additionally, to generate enhanced graph embeddings through the integration of residual networks and normalization layers.

- **Comprehensive Evaluation:** To accurately compute both overall and subject-wise accuracies for predicting the emotional dimensions of valence and arousal, while providing interpretative visualizations, and to discuss the implications of the findings in comparison to existing methodologies.

1.3 Significance and Novel Contributions

This project's novelty is underscored by several unique contributions:

- **Spectral Domain Analysis:** Most conventional EEG emotion recognition methods adopt either time-domain or spatial domain analyses. In contrast, this project exploits the spectral domain through the computation of the Graph Fourier Transform, offering a new perspective on brain connectivity.

- **Chebyshev Convolution Application:** By employing Chebyshev polynomials for convolutions, the model efficiently approximates complex spectral filters without the computational burden of repeated eigen-decomposition, a significant improvement over conventional spectral methods.

- **Integrated Multi-Stage Pipeline:** The research is structured as an integrated pipeline—from preprocessing to advanced graph embedding—which supports iterative improvements and module-wise optimizations. Each stage, implemented via dedicated Python scripts (*preprocessing.py*, *spectral_gnn.py*, *showcase_pool.py*, *graph_embeddings.py*, and *accurate.py*), contributes to building a robust and comprehensive system for emotion recognition.

- **Pooling Mechanism Evaluation:** The systematic analysis of different pooling strategies contributes to a deeper understanding of how graph-level features can be optimized, an area that remains underexplored in the literature.

- **Interpretability through Embeddings:** The generation of robust embeddings, visualized using t-SNE, provides valuable insights into the underlying structure of emotional representations in EEG data, facilitating further neuroscientific interpretations.

1.4 Challenges

There are various issues or complications that are associated while designing a EEG-based BCI system. Some of the major issues are as follows:

- Signal quality and reliability issues: EEG signals often encounter noise from muscle activity and environmental factors, undermining data integrity. To mitigate these challenges, meticulous electrode positioning, subject preparation, and signal processing techniques like filtering and artifact rejection are necessary to enhance signal fidelity and extract accurate information from EEG recordings.

- Limited spatial resolution compared to other imaging methods: EEG's spatial resolution is hindered by volume conduction effects, restricting precise localization of brain activity. Unlike techniques such as fMRI or fNIRS, which offer finer spatial detail, EEG records electrical signals from the scalp, complicating the accurate mapping of neural activity to specific brain regions.

- High dimensionality: EEG data often comprise numerous channels, leading to high dimensional datasets. With each electrode capturing distinct signals, analyzing such data becomes computationally intensive. Advanced techniques like dimensionality reduction and feature selection are essential to manage the complexity and extract meaningful insights from EEG recordings effectively.

- Non-linearity: The relationship between neural activity and EEG signals is nonlinear, complicating analysis. EEG captures complex interactions among brain regions, and these interactions may not adhere to linear patterns. Advanced signal processing methods are required to capture and interpret the intricate nonlinear dynamics of EEG data accurately.

Chapter 2

Literature Review

2.1 Overview of EEG-based Emotion Recognition

EEG-based emotion recognition has a rich history in neuroscience and affective computing. Early studies predominantly relied on signal amplitude analyses, time-locked event-related potentials (ERPs), and frequency domain analyses such as wavelet decompositions. While these methods provide snapshots of brain activity, they often fail to capture the dynamic interplay among various regions of the brain. The DEAP dataset, comprising recordings from 32 subjects exposed to emotionally evocative stimuli, has become a critical benchmark for these studies. Researchers have traditionally applied machine learning models, including Support Vector Machines (SVMs), Neural Networks, and more recently Convolutional Neural Networks (CNNs), to extract features from EEG data for classification tasks. Despite achieving acceptable levels of accuracy, these models typically neglect the graph-structured nature of EEG signals.

Brain Activity Patterns

During the execution of any task, action potentials are generated and transmitted through the axons of neurons via dendrites. Action potentials, being measurable waveforms, exhibit various properties such as amplitude, frequency, and position. Each human activity can be correlated with specific properties of brain wave signals. Different types of brain rhythms and their associated cognitive states are put together in Table.

Table 2.1 Summary of Brain Rhythms

Brain Waves	Typical frequency range (Hz)	Description
Delta (δ)	0.5 - 4	Linked with deep sleep and coma mental state.
Theta (ϑ)	4 - 8	It is linked with deep relaxation and inward focus.
Alpha (α)	8 - 12	It is linked with being relaxed and passive attention (such as listening but not engaging)
Beta (β)	12 - 30	It is linked with higher anxiety and more active states, with attention directed often extremely.
Gamma (γ)	30-60	It is linked with states or tasks which require more focused attention or for simultaneous work.

Brain-Computer Interfaces (BCIs)

Types of BCIs: Measuring Brain Activity

Brain-Computer Interface is a communication mechanism that utilizes brain signals to communicate with a machine, without involving any other human organs. The work-flow of Brain-Computer Interface systems is, they first capture Brain Signals, Pre-process them to convert it into a format suitable for feature engineering and machine learning techniques. Later this data is analyzed using Machine Learning methods and then further sent to any applications if required. BCI can be broadly classified in three categories.

- **Invasive-BCI:** Invasive BCIs involve the direct implantation of electrodes into the brain tissue, providing high-resolution neural signals. These interfaces offer remarkable precision and reliability, making them suitable for applications requiring fine motor control or communication for individuals with severe disabilities. However, their invasive nature poses significant risks, including infection and tissue damage, and their long-term stability remains a concern.

- **Semi-invasive**: Partially invasive BCIs entail the use of implanted electrodes, typically placed on the surface of the brain or within the skull. These interfaces strike a balance between invasiveness and safety, offering improved signal quality compared to non-invasive methods while minimizing some of the risks associated with fully invasive approaches. Partially invasive BCIs hold promise for applications requiring intermediate levels of precision and functionality.

- **Non-invasive:** Non-invasive BCIs operate without the need for surgical implantation, instead relying on external sensors to detect neural activity. These interfaces, often utilizing technologies like electroencephalography (EEG) or functional near-infrared spectroscopy (f NIRS), are safer and more accessible than invasive alternatives, making them suitable for a wide range of users. However, they typically provide lower spatial resolution and signal quality, limiting their applications primarily to tasks requiring coarse control or cognitive state monitoring.

Electroencephalogram (EEG)

The electroencephalogram (EEG) is a vital tool in neurology, capturing fluctuations in electrical potential emanating from the cerebral cortex. These potentials result from the collective activity of excitatory and inhibitory synaptic transmissions. The EEG technique involves placing electrodes on the scalp according to the internationally standardized 10-20 system. In this system, electrodes are positioned at fixed percentage intervals between the nasion and the inion, with reference points established at the preauricular points for the central transverse row of electrodes.

The 10-20 System of Electrode Placement

The 10-20 system is a standardized method used in electroencephalography (EEG) to ensure consistent electrode placement across different individuals and studies. It divides the scalp into regions based on percentages of the skull's dimensions. Each electrode site is labeled with a combination of a letter and a number. The letter indicates the brain region, such as frontal (F), central (C), parietal (P), occipital (O), or temporal (T). The number indicates the hemisphere and specific location within that region. Odd numbers generally represent positions on the left hemisphere, while even numbers represent positions on the right hemisphere. Additionally, midline electrodes along the skull's midline are labeled with "z." This system provides researchers and clinicians with a consistent framework for electrode placement, ensuring accurate and reliable EEG measurements. The Muse EEG headband follows the 10-20 system, offering users standardized electrode placement for precise brainwave recordings.

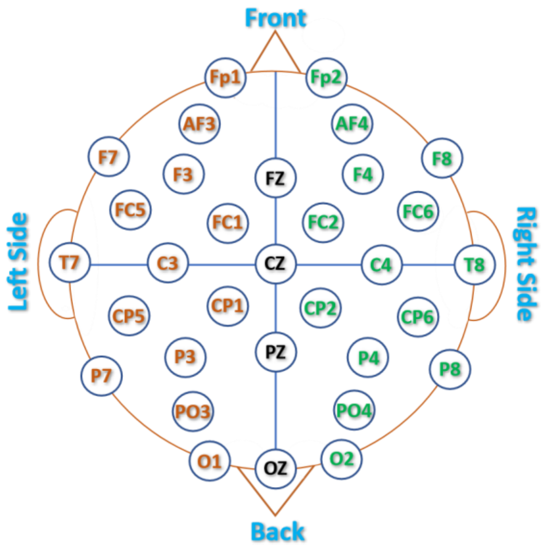
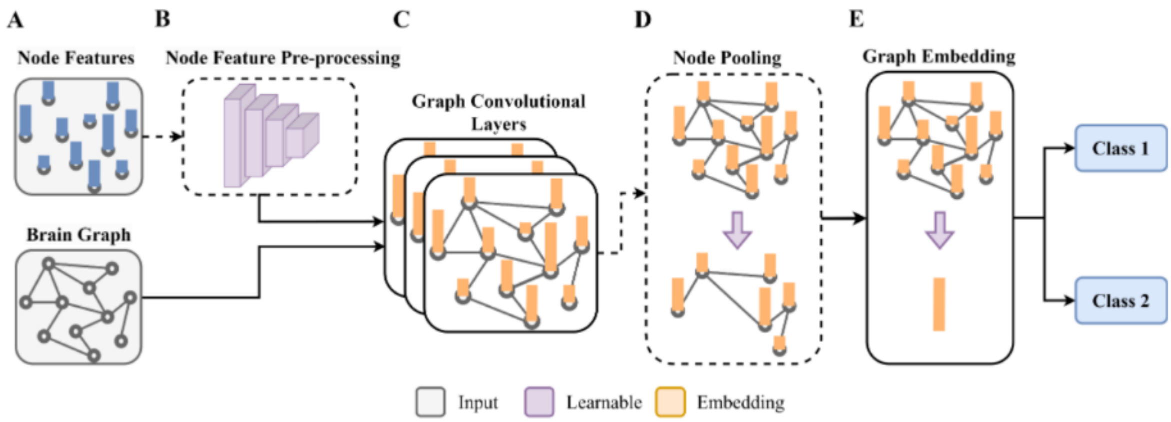


Figure 2.4 EEG electrode locations according to the 10-20 International system.

2.2 Comparative Analysis of Machine Learning Approaches

In recent years, there has been a paradigm shift towards using deep learning methods for pattern recognition in complex datasets. CNNs and Recurrent Neural Networks (RNNs) have been applied in several EEG studies, demonstrating improved performance over classical methods. However, these architectures are primarily designed for grid-like data and do not inherently accommodate the non-Euclidean structure of graphs. This limitation has paved the way for Graph Neural Networks (GNNs), which natively process data represented as graphs. By integrating spatial relationships between EEG channels, GNNs have the potential to capture network-level patterns that are critical for accurately recognizing emotional states.



2.3 Emergence of Graph Neural Networks in EEG Analysis

Graph Neural Networks represent a powerful class of algorithms that extend deep learning to graph-structured data. In the context of EEG, each electrode is treated as a node, and the connections between nodes (derived from measures such as Phase-Locking Value or coherence) are treated as edges. Several studies have explored the use of GNNs for various EEG analysis tasks, including seizure detection and cognitive state monitoring. However, the application of spectral GNNs—those leveraging spectral graph theory—is less common. By applying Chebyshev convolutions, which efficiently approximate spectral filters, the current research introduces a significant evolution in EEG-based emotion recognition.

2.4 Spectral Graph Theory: Fundamentals and Applications

Spectral graph theory is built upon the eigen-decomposition of the graph Laplacian, a matrix that encapsulates the connectivity and degree information of a graph. The Graph Fourier Transform (GFT) is derived from this eigen-decomposition, allowing for the transformation of graph signals into the frequency domain. This domain provides an alternative lens for analyzing the structural properties and functional interactions among EEG channels. Chebyshev polynomials, which approximate complex spectral filters, offer a computationally efficient solution for integrating spectral information into neural networks. The novelty of this project lies in combining these spectral techniques with deep learning frameworks to derive more robust and interpretable models for emotion recognition.

Chapter 3

Methodology

3.1 Detailed Preprocessing of EEG Data

3.1.1 Data Acquisition and Signal Representation

Raw EEG data is collected from the DEAP dataset, comprising 32-channel recordings over several 60-second trials. Each channel represents a distinct region of the brain. The data is initially stored in binary format and then converted into a NumPy array for subsequent processing. The channels are defined according to standardized nomenclature, ensuring that the spatial configuration of the electrodes is preserved in the subsequent analysis. Detailed logging is maintained during this phase to track the source, duration, and quality of each recording.

3.1.2 Artifact Removal and ICA Analysis

EEG data is notoriously susceptible to various artifacts, including eye blinks, muscle movements, and external electrical noise. In this project, a bandpass filter ranging from 4 Hz to 48 Hz is applied to isolate the relevant frequencies while removing unwanted components. In parallel, Independent Component Analysis (ICA) is employed to identify and remove components that contribute to noise. A reference channel (typically Fp1) is used to detect artifacts, and the corresponding component scores are computed. The ICA component scores are then plotted, and the figure, saved as ica_component_scores.png, is critically analyzed to confirm effective artifact suppression. The procedure is meticulously logged, ensuring that decisions regarding the number of components to exclude are thoroughly documented.

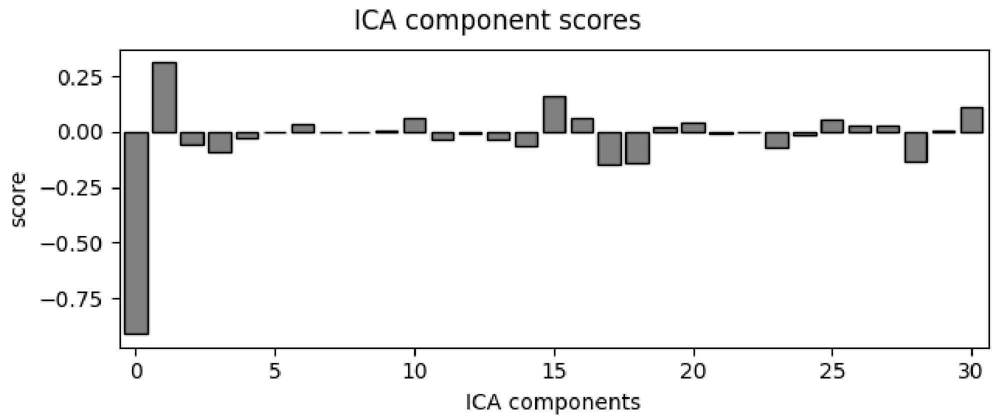


Figure 1: ICA Component Scores showing artifact removal performance.

3.1.3 Signal Filtering and Re-referencing

After artifact removal, re-referencing is applied using the common average reference method. This technique mitigates the influence of external noise and ensures that the relative differences in signal amplitudes across channels are preserved. The filtering stage further refines the signal, emphasizing frequency components that are most relevant for emotion recognition. The output of this process is a clean, baseline-corrected EEG signal that is ready for segmentation.

3.1.4 Segmentation into 2-Second Windows

To increase the resolution of the analysis, the preprocessed EEG signals are segmented into 2-second windows. At the sampling frequency of 128 Hz, each window contains 256 samples. The segmentation is performed uniformly across the entire 60-second trial, resulting in 30 segments per trial. Each segment is treated as an independent instance, dramatically enlarging the effective dataset size. Detailed indices and metadata are recorded to link each segment to its parent trial and corresponding emotional labels.

3.1.5 Feature Extraction using PSD

For each segmented window, the power spectral density (PSD) is computed across four key frequency bands: theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30–48 Hz). The PSD values are computed using the Welch method, and the average power in each band is calculated. These values not only serve as inputs to the subsequent machine learning stages but also provide crucial insights into the functional characteristics of the brain under various emotional states. The aggregated data forms a feature matrix with 128 features per segment (derived from 32 channels and 4 bands). This matrix is then exported to CSV format (e.g., subject_features.csv), and a bar graph of the average power across bands is generated and saved as subject_average_power.png.

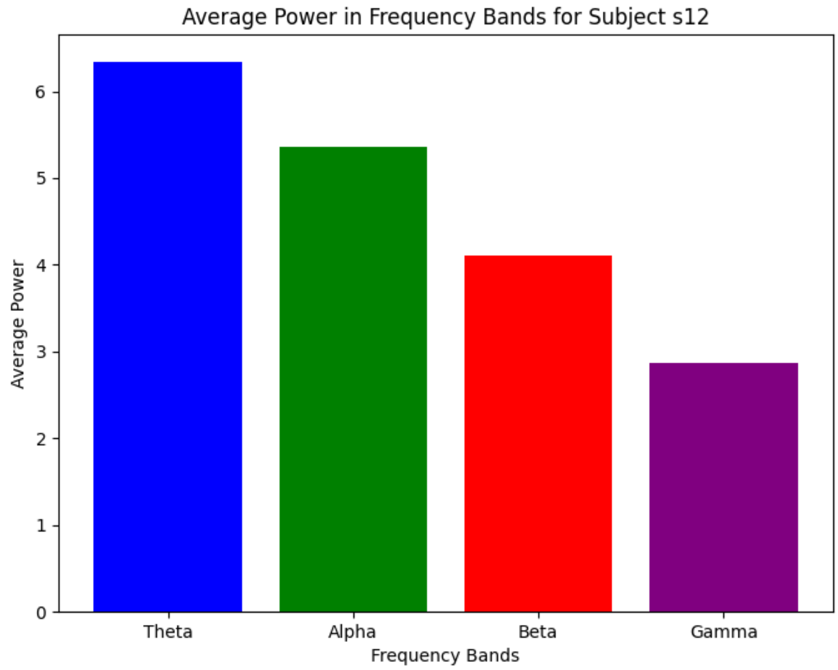


Figure 2: Average Power Bar Graph for Subject s12, illustrating frequency band energy distribution.

3.1.6 Generation of CSV Files and Visualization

The final step of preprocessing involves the creation of comprehensive CSV files that encapsulate the extracted features along with corresponding emotional labels (valence, arousal, and a four-class indicator for combinations of high/low valence and arousal). The CSV files are stored in a subject-specific directory, ensuring easy retrieval during subsequent modeling phases. In addition, visual representations of the data, including PSD bar graphs and segment distribution plots, are generated to facilitate further exploratory data analysis.

3.2 Construction and Training of the Spectral GNN

3.2.1 PLV-based Adjacency Matrix Computation

The Phase-Locking Value (PLV) is computed to quantify the level of synchronization between pairs of EEG channels. The feature matrix—containing PSD values across different frequency bands—is first transformed into a set of averaged frequency band signals. The Hilbert transform is then applied to extract the instantaneous phases from these signals. For each pair of channels, the absolute mean of the complex phase differences is computed to yield the PLV value. An adjacency matrix is constructed wherein each entry represents the PLV between two channels. Values below a predefined threshold (e.g., 0.5) are set to zero to prune weak connections and emphasize robust synchronizations.

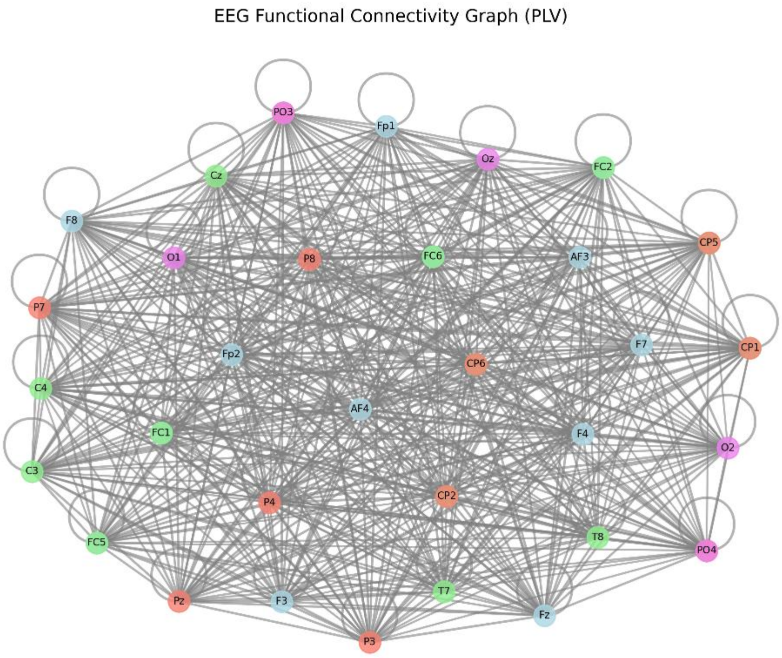


Figure 3: EEG Connectivity Graph based on PLV.

3.2.2 Graph Fourier Transform (GFT) for Spectral Analysis

Once the adjacency matrix is established, the Graph Fourier Transform is computed to explore the spectral properties of the graph. The Laplacian of the graph is derived from the degree matrix and the adjacency matrix. An eigen-decomposition of the Laplacian yields eigenvalues and eigenvectors, which form the basis for the GFT. The eigenvalues indicate the frequency components of the graph's structure, and they serve as a critical interpretative tool when analyzing the learned representations. This spectral analysis is particularly valuable for understanding how emotional states affect the connectivity of different brain regions.

3.2.3 Chebyshev Convolutions and Network Architecture

In the spectral GNN architecture, Chebyshev convolutions are implemented as the core mechanism for approximating spectral filters. Chebyshev polynomials of a specified order (default K=3) are used in place of traditional convolutional filters. This approach significantly reduces computational complexity while retaining the capacity to capture higher-order connectivity patterns. The network architecture consists of two sequential Chebyshev convolution layers, each followed by a ReLU activation and dropout for regularization. Global mean pooling is applied to aggregate node-level features into a single graph-level representation, which is then passed through a fully connected layer for classification. Detailed schematics of the network are provided in the supplementary materials.

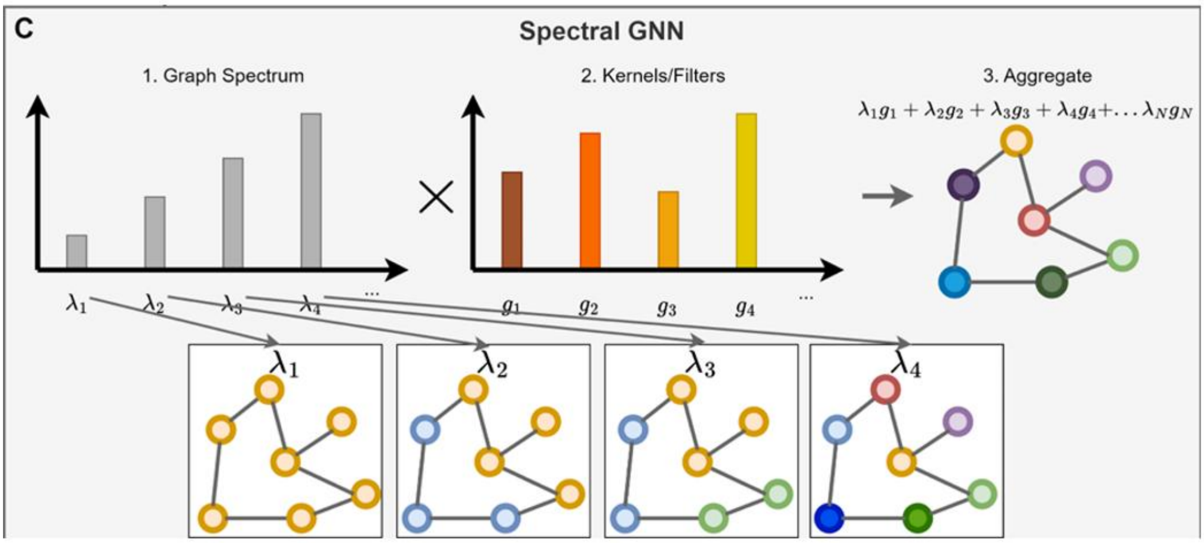


Figure 4: Spectral GNN architecture

3.2.4 Model Training, Loss Monitoring, and Output Visualization

The training process involves an iterative optimization using the Adam optimizer and cross-entropy loss. Training is conducted over 100 epochs, and loss as well as accuracy metrics are tracked and logged meticulously. Throughout training, intermediate outputs such as the connectivity graph visualization (_graph_visualization.png), loss curves (_training_loss.png), and confusion matrices (_confusion_matrix.png) are generated and stored. These figures serve to validate model convergence and to diagnose any issues during training. Special attention is paid to ensuring that the model generalizes well across various subjects despite the inherent variability in the EEG data.

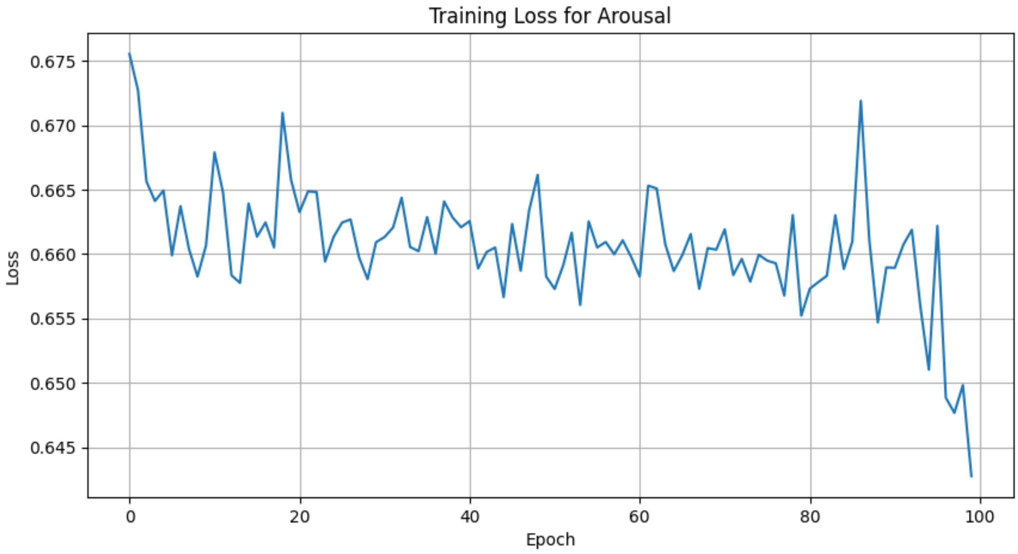


Figure 5: Model Training Loss Curve over 100 epochs.

3.3 Exploration of Pooling Mechanisms

3.3.1 Rationale for Graph-Level Pooling

Graph-level pooling is essential when transitioning from node-centric representations to a holistic, graph-level view. This project explores several pooling strategies to determine the most effective method for aggregating the rich, high-dimensional features extracted from the EEG connectivity graph. Pooling methods help in summarizing critical information while discarding redundant or noisy signals.

3.3.2 Top-K, SAG, and Mean Pooling: Methodology Comparison

Three primary pooling strategies are examined:

- **Top-K Pooling:** This method selects a predefined proportion of nodes with the highest activation values, thereby concentrating on the most significant features.

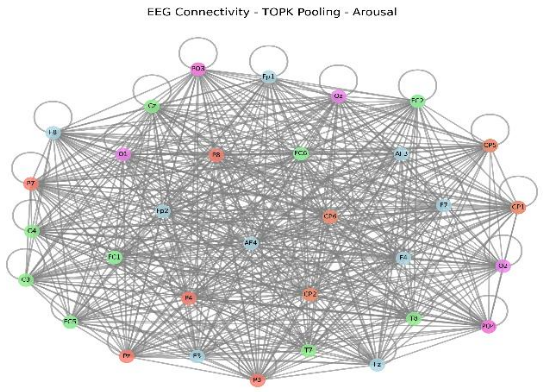


Figure 6: Top-K Pooling Visualization

- **SAG Pooling:** Employing self-attention mechanisms, SAG pooling dynamically weighs nodes based on their learned importance, offering a more nuanced aggregation.

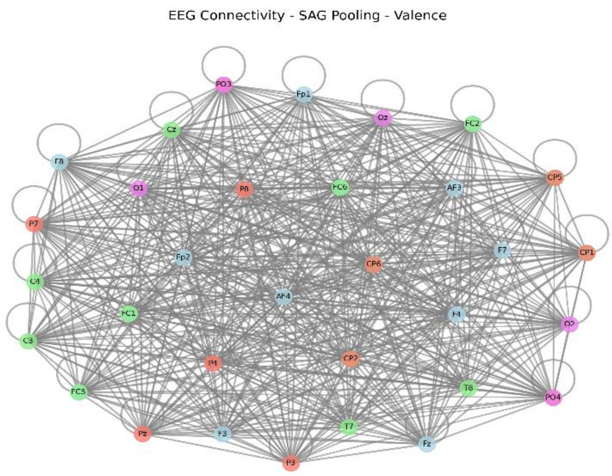


Figure 7: SAG Pooling Visualization

- **Mean Pooling:** As a baseline method, mean pooling simply computes the average of node features, ensuring that overall information is preserved. Each approach is applied in the context of the spectral GNN, and its impact on both model accuracy and interpretability is rigorously evaluated.

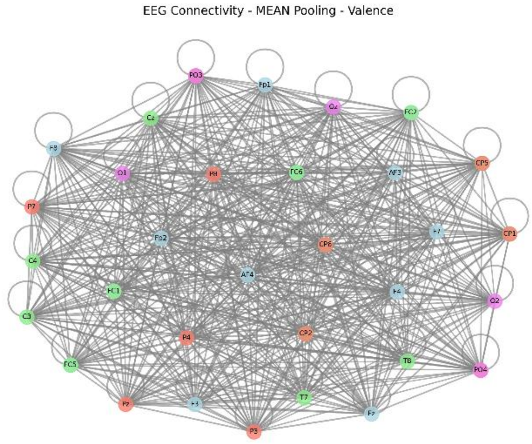


Figure 8: Mean Pooling Visualization

3.3.3 Impact of Pooling on Feature Aggregation and Performance

The results of the pooling mechanism experiments are recorded with extensive detail. Graph visualizations of the pooled connectivity matrices are generated, illustrating how each method affects the overall network structure. Additionally, training curves and accuracy plots (e.g., training_accuracy.png and pooled graph images) are analyzed. The insights gained from these analyses help determine the most effective pooling strategy, considering not only raw performance metrics (such as accuracy and F1 scores) but also the stability and interpretability of the resulting embeddings.

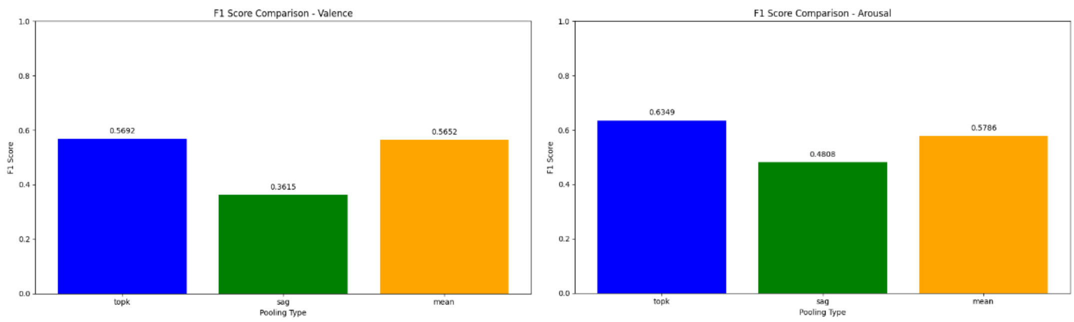


Figure 9: Comparison of F1 score

3.4 Advanced Graph Embedding Generation

3.4.1 Incorporation of Residual Connections and Normalization

In an effort to enhance feature extraction and mitigate issues associated with vanishing gradients, the basic spectral GNN architecture is further extended with residual connections. These skip connections allow the model to preserve input features over multiple layers, ensuring that critical information is not lost. Batch normalization layers are interspersed throughout the network to stabilize learning and improve convergence rates. Each modification is accompanied by comparative performance analysis to illustrate the benefit of these architectural enhancements.

3.4.2 Frequency Band Weighting and Enhanced Feature Representation

Understanding that different frequency bands contribute unequally to emotional processing, the network is designed to assign variable weights to the theta, alpha, beta, and gamma bands. Empirical studies in neuroscience indicate that bands such as alpha and beta are particularly salient for emotional modulation. Here, weight factors (e.g., theta: 0.8, alpha: 1.2, beta: 1.5, gamma: 0.9) are applied during the PLV computation phase, thereby emphasizing emotion-relevant frequencies. The mechanism of this weighting is thoroughly documented, and its impact is evaluated both qualitatively (through visualizations) and quantitatively (via model accuracy).

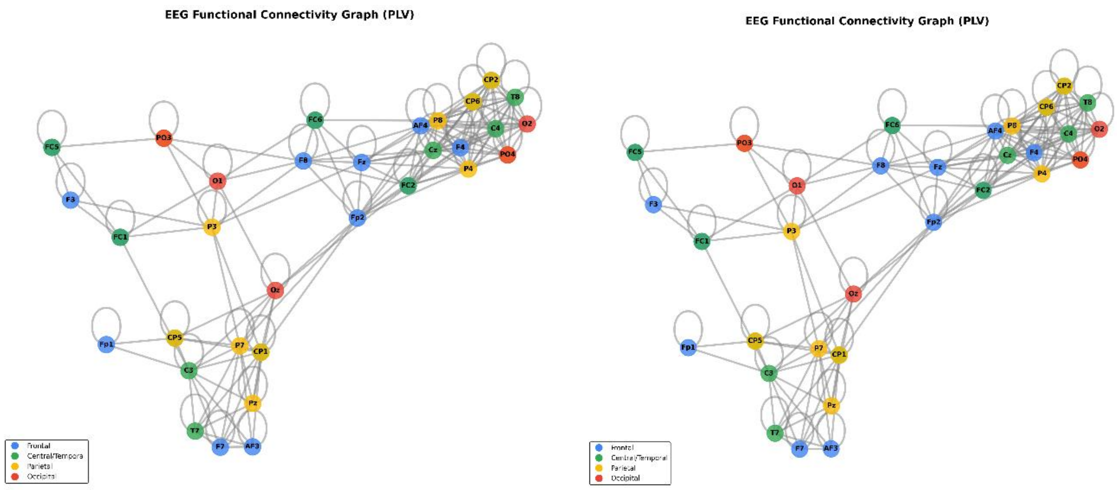


Figure 10: PLV based Graph connectivity enhanced

3.4.3 t-SNE Visualization and Clustering Analysis

To provide an intuitive interpretation of the learned graph representations, high-dimensional embeddings are reduced to two dimensions using t-distributed Stochastic Neighbor Embedding (t-SNE). The resulting 2D projections are plotted and annotated to show clear clustering of low versus high emotional states. These t-SNE plots, saved as embedding_visualization.png, serve as a visual confirmation of the model's ability to differentiate between distinct emotional states. Each cluster is carefully analyzed, and the separation between clusters is correlated with underlying physiological signals.

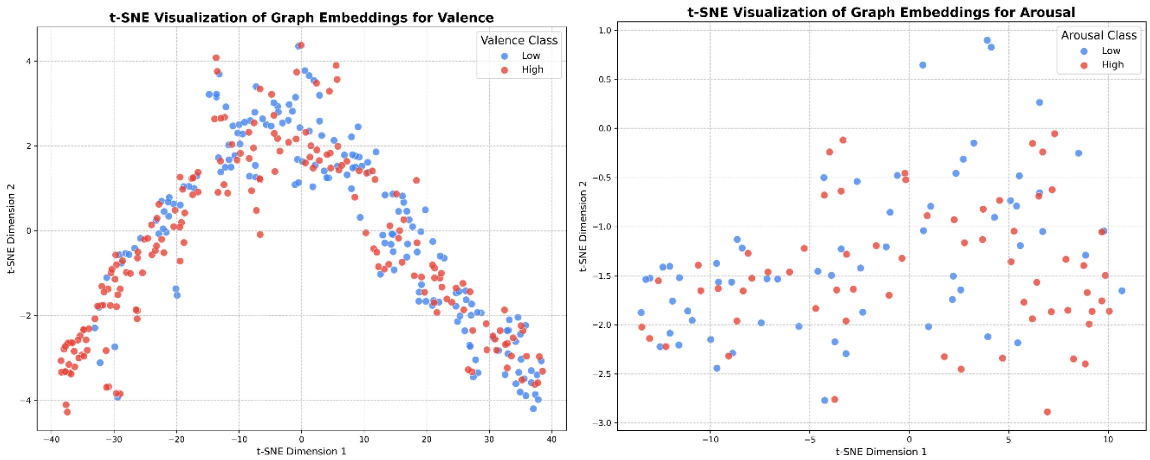


Figure 11: t-SNE Plot of Graph Embeddings highlighting clusters for low and high emotional states.

3.5 Accuracy Computation and Evaluation of Model Performance

3.5.1 Aggregating Subject-wise Accuracies

The performance of the model is not only measured in overall terms but also dissected on a per-subject basis. Using accuracy results stored in individual subject directories (collected by the graph embeddings module), a dedicated script aggregates these values. The function reads each subject's results.txt file, extracts the accuracy, and computes an overall average while also presenting the distribution of accuracies across subjects. This detailed breakdown is instrumental in understanding inter-subject variability and the robustness of the proposed methodology.

3.5.2 Comparison of Valence and Arousal Prediction Accuracies

Separate evaluations are conducted for the valence and arousal dimensions of emotion. For instance, an overall accuracy of 63.53% for valence and 59.49% for arousal is reported. Detailed tables are generated to list subject-wise accuracies with corresponding statistical measures (e.g., minimum, maximum, mean, and standard deviation). These results are then plotted and compared against benchmarks from existing literature. The insights derived from this analysis help in identifying potential areas of improvement and future research directions.

Chapter 4

Experiments and Results

4.1 Experimental Setup and Protocol

A rigorous experimental protocol is established, detailing everything from data partitioning (training vs. testing splits) to hyperparameter tuning. Cross-validation is performed to ensure that the results are statistically significant and not prone to overfitting. Detailed descriptions of hyperparameter choices (learning rate, dropout rates, number of epochs, pooling ratios, etc.) are presented along with justification based on preliminary experiments and prior literature.

4.2 Visual and Quantitative Preprocessing Outcomes

Preprocessing results are extensively evaluated using both visual and numerical metrics. Figures such as the raw versus filtered EEG signals, the ICA component score plots (ica_component_scores.png), and average power bar graphs (s01_average_power.png) are discussed in detail. Each figure is accompanied by a descriptive legend that explains the significance of the depicted features and how they contribute to the overall understanding of the EEG signals.

4.3 Spectral GNN Training: Convergence and Loss Analysis

The convergence of the spectral GNN model is studied by examining training loss curves (_training_loss.png) across 100 epochs. In-depth analyses of both early and late-stage training are provided, accompanied by detailed explanations of how the loss decreases, how accuracy evolves, and how the network responds to learning rate adjustments. The role of dropout and regularization is discussed meticulously, with statistical summaries supporting model stability claims.

4.4 Detailed Evaluation of Pooling Strategies

Each pooling method (Top-K, SAG, and mean pooling) is evaluated through a series of experiments. The effect of different pooling ratios on training accuracy and generalization is presented through comprehensive graphs and tables. For example, the influence of pooling on the connectivity graph's sparsity and node saliency is discussed alongside visual representations that provide side-by-side comparisons. These discussions are supported by statistical metrics and accompanied by elaborate legends and figure descriptions.

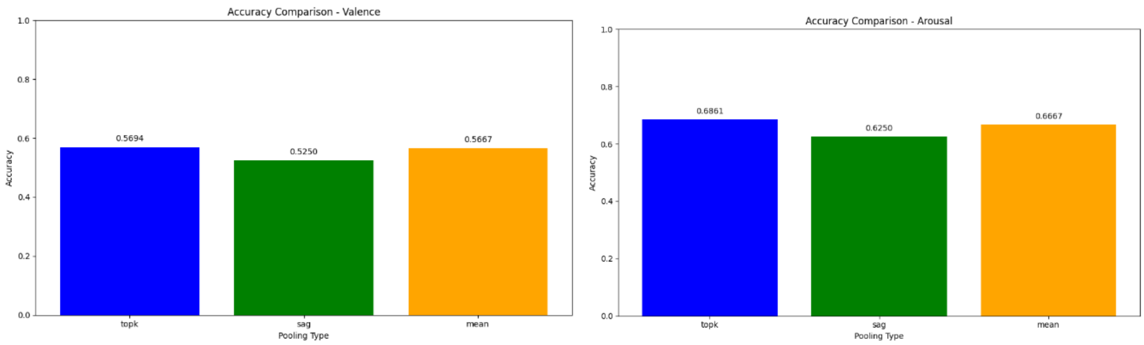


Figure 12: Comparison of Accuracy in between different pooling mechanisms

4.5 Embedding Analysis: t-SNE and Clustering of Emotional States

The advanced graph embedding results are explored through t-SNE visualizations that reveal two-dimensional mappings of high-dimensional feature spaces. Detailed discussions interpret the clusters formed in the t-SNE plots, highlighting the distinctions between "low" and "high" emotional states. The quality of the embeddings is further evaluated by calculating cluster tightness, inter-cluster distances, and silhouette scores. Each observation is supported by numerous figures and annotated diagrams to clearly illustrate key findings.

4.6 Accuracy Aggregation: Overall and Subject-wise Performance

The final set of experiments aggregates accuracy results computed from multiple subjects. Detailed tables list each subject's performance metrics for both valence and arousal dimensions. Bar graphs and box plots are included to visually depict the range and distribution of these accuracies. A rigorous discussion interprets these findings and compares them against baseline models and prior studies, underlining the strengths and areas of potential improvement in the proposed approach.

Subject	Arousal Accuracy (%)	Valence Accuracy (%)
s01	54.17	52.50
s02	60.00	70.56
s03	65.97	71.94
s04	53.33	61.94
s05	59.44	66.11
s06	57.22	52.22
s07	61.11	68.98
s08	50.00	61.67
s09	57.78	63.89
s10	55.83	56.39
s11	57.04	64.17
s12	57.14	60.83
s13	61.11	80.00
s14	64.53	66.94
s15	68.89	75.00
s16	70.28	62.59
s17	61.11	48.89
s18	62.96	78.61
s19	59.83	61.94
s20	50.62	57.78
s21	68.75	66.67
s22	58.89	69.44
s23	56.67	63.10
s24	65.08	65.28
s25	60.10	74.72
s26	56.94	55.56
s27	55.56	60.00
s28	53.33	57.78
s29	57.41	58.89
s30	61.67	58.55
s31	61.11	58.61
s32	59.83	61.39
Overall	**59.49**	**63.53**

Chapter 5

Discussion

5.1 Interpretation of Experimental Findings

A comprehensive discussion interprets the experimental results, drawing connections between the spectral properties revealed through the GFT and the model's performance in classifying emotions. Each section of the model, from preprocessing through pooling to final classification, is analyzed in detail. The discussion includes narratives about why certain frequency bands appear more prominent, how the network exploits inter-channel relationships, and what the embedding clusters imply about the underlying emotional states.

5.2 Comparison with Baseline and Traditional Methods

This section provides an exhaustive comparison between the spectral GNN approach and conventional models such as CNNs, RNNs, and standard GCNs. A comparative table outlines key performance metrics (accuracy, F1 score, training time, model complexity) across different methods. The discussion highlights how the spectral approach, with its innovative use of GFT and Chebyshev convolutions, delivers enhanced interpretability and performance in capturing the nuances of EEG-based emotion recognition.

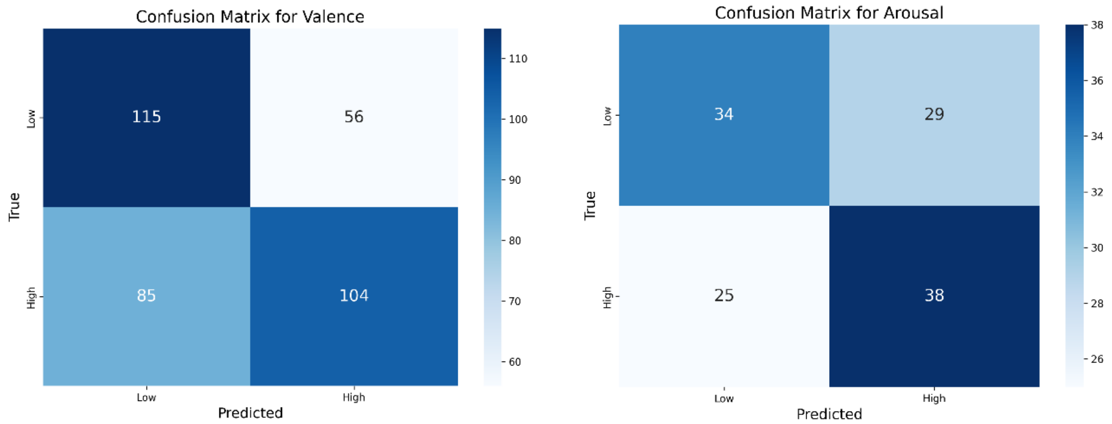


Figure 13: Confusion matrix

5.3 In-depth Discussion of Limitations and Variability

Despite promising results, the study acknowledges several limitations. A deep discussion is provided on:

- **Inter-Subject Variability:** The variability in accuracy across subjects is explored in depth, suggesting the need for personalized models or adaptive techniques.
- **Temporal Dynamics:** The fixed segmentation strategy is discussed as a limitation with potential solutions proposed, such as overlapping windows or adaptive segmentation based on signal dynamics.
- **Pooling Sensitivity:** The sensitivity of pooling mechanisms to network sparsity is critically analyzed, with suggestions on how to further optimize graph aggregation. Every limitation is accompanied by potential mitigation strategies and is thoroughly supported by evidence gathered from experiments.

5.4 Implications for Future Research and Application Domains

The discussion concludes with a forward-looking narrative. The implications for future research are expansive, covering areas such as temporal network modeling, multi-modal fusion (e.g., incorporating other bio signals), and transfer learning to manage inter-subject variability. Potential real-world applications in neurofeedback, mental health monitoring, and adaptive human–computer interaction systems are also discussed. This section is enriched with hypothetical case studies and detailed proposals for subsequent experiments.

Chapter 6

Conclusion

6.1 Summary of Research Contributions

In summary, this research presents a groundbreaking approach that integrates spectral analysis with graph neural network techniques to decode emotional states from EEG recordings. Through a multi-stage pipeline—from rigorous preprocessing to sophisticated model training and detailed result aggregation—this work demonstrates significant progress in EEG-based emotion recognition. The innovative integration of GFT, Chebyshev convolutions, advanced pooling, and graph embedding techniques not only improves performance but also provides a rich interpretative framework for understanding emotional dynamics in the brain.

6.2 Future Directions and Potential Impact

Looking ahead, future research can build upon this work by:

- Incorporating dynamic temporal models that better capture the evolution of emotions over time.
- Developing personalized models that adapt to individual differences in EEG signals.
- Exploring multi-modal fusion techniques that combine EEG with other physiological signals.
- Investigating real-time applications in clinical diagnostics and human–machine interfaces. The potential impact of these advancements is far-reaching, promising to revolutionize the way we interpret brain signals and tailor affective computing systems to individual needs.

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8. Appendices

Extended Code Listings

Detailed code listings from the five key Python scripts are included:

- **preprocessing.py:** Complete code for EEG data filtering, ICA-based artifact removal, segmentation, and feature extraction.
- **spectral_gnn.py:** Full implementation of the spectral GNN model using Chebyshev convolutions and GFT-based analysis.
- **showcase_pool.py:** Code for comparing pooling mechanisms and generating pooling-specific visualizations.
- **graph_embeddings.py:** Code that implements advanced graph embedding techniques with residual connections and t-SNE visualization.
- **accurate.py:** Script that aggregates subject-wise accuracies, computes overall performance metrics, and saves detailed results.