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**Bayesian-Graph Fourier Analysis Network: Lightweight
Model for Epilepsy Detection and Comparison with
Attention-Enhanced ConvNeXt-BiLSTM**

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August, 2025**

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Authors

Abstract

This study proposes a dual-methodology framework for epileptic seizure detection using EEG signals. The first method leverages an **Attention-Enhanced ConvNext-BiLSTM network** to capture spatial and temporal features through advanced attention mechanisms. The second introduces **B-GFAN, a novel, lightweight Bayesian-Graph Fourier Analysis Network** that combines spectral graph theory, Fourier analysis, and Bayesian uncertainty quantification with four specialized attention modules to deliver clinically reliable and interpretable predictions. Evaluated on the CHB-MIT EEG dataset, results show that while ConvNext-BiLSTM achieves robust conventional performance, B-GFAN offers superior clinical utility with uncertainty-aware predictions, computational efficiency, and enhanced interpretability. This work contributes to the advancement of mathematically grounded, uncertainty-guided clinical decision support systems for epilepsy detection.

Contents

	PAGE
Title Page	i
Acknowledgement	ii
Abstract	iii
Contents	iv
List of Tables	v
List of Figures	vi
CHAPTER I Work Distribution	1
CHAPTER II Introduction	2
• Background	2
• Problem Statement	2
• Objectives	2
• Scope	3
• Unfamiliarity of the Problem	5
• Project Planning	6
• Financial Analyses and Budget	6
• Applications	6
• Organization of Report	7
• Summary	8
CHAPTER III Literature Review	9
• Introduction	9
• Relevant Terminology	9
• Related Works	11
CHAPTER IV Background Analysis	20
• Preprocessing Techniques for EEG Data	20
• Neural Network Architectures for EEG Analysis	23
• Graph Signal Processing and Spectral Graph Theory	29
• Fourier Analysis Networks	30
• Graph Attention Networks	32
• Bayesian Neural Networks and Uncertainty Quantification	33
• Multi-Modal Attention Mechanisms	34
• Uncertainty Propagation in Neural Networks	35
• Summary	36
CHAPTER V Methodology	37
• Epilepsy Detection Using attention enhanced ConvNeXt-BiLSTM Dual Branch Network	37

• Epilepsy Detection Using Bayesian Graph Fourier Analysis Networks (B-GFAN) with Multi-Modal Attention and Uncertainty Quantification	40
CHAPTER VI Implementation, Results and Discussions	47
• Introduction	47
• Dataset Description	47
• Evaluation Metrics	47
• Implementation	49
• Results	49
• Objective Achieved	65
• Summary	67
CHAPTER VI Societal, Health, Environment, Safety, Ethical, Legal and Cultural Issues	68
• Intellectual Property Considerations	68
• Ethical Considerations	68
• Safety Considerations	68
• Legal Considerations	68
• Impact of the Project on Societal, Health, and Cultural Issues	69
• Impact of the Project on the Environment and Sustainability	69
CHAPTER VII Addressing Complex Engineering Problems and Activities	70
• Complex Engineering Problems	70
• Complex Engineering Activities	71
CHAPTER VIII Conclusions	73
• Conclusion and Challenges Faced	73
• Future Works	74
References	77

List of Tables

Table No.	Description	Page
1.1	Work Distribution between Group Members	1
3.1	A brief summary of CNN-LSTM based methods for epilepsy detection using EEG signals	16
3.2	Comparative analysis of Graph Neural Network-based methods for epileptic seizure detection	16
3.3	Comparative analysis of Fourier-based methods for epileptic seizure detection	18
5.1	Parameter Counts and FLOPs for Each Component of the Attention enhanced ConvNeXt-BiLSTM Architecture.	40
5.2	Parameter Counts and FLOPs for Each Component of the B-GFAN Architecture.	46
5.3	Computational Efficiency Metrics for B-GFAN Network.	46
6.1	Information about Database CHB-MIT of this study.	48
6.2	Training Configuration and Hyperparameters for ConvNext-BiLSTM Dual Branch Network.	49
6.3	Detailed performance indexes for across-subject experiment using ConvNext-BiLSTM Network.	50
6.4	Detailed performance indexes for LOSO experiment using ConvNext-BiLSTM Network.	50
6.5	Inference Time and Throughput for attention enhanced ConvNext-BiLSTM.	50
6.6	Ablation Study Results for Attention enhanced ConvNext-BiLSTM Network.	52
6.7	Detailed performance indexes for across-subject experiment using B-GFAN Network.	53
6.8	Detailed performance indexes for LOSO experiment using B-GFAN Network.	53
6.9	Inference Time and Computational Efficiency for B-GFAN Network.	53
6.10	Uncertainty Quantification Metrics for B-GFAN Network.	55
7.1	Complex Engineering Problems Associated with the Dual-Methodology Thesis	71

List of Figures

Figure No.	Description	Page
2.1	A preliminary timeline of the thesis.	6
4.1	Continuous Wavelet Transform (CWT) Process for EEG.	22
4.2	CWT Visualization of EEG Segment.	23
4.3	ConvNeXt-Tiny Model Architecture.	24
4.4	LSTM Network Structure for Capturing Temporal Features.	26
4.5	BiLSTM Network Structure for Capturing Temporal Features.	26
4.6	SEBlock for Highlighting Important Feature Channels.	27
4.7	MultiHead Self Attention Mechanism for Focusing Important Features.	28
4.8	Graph Laplacian construction and eigendecomposition process for EEG electrode networks.	30
4.9	Graph spectral filtering process and its effect on different spatial frequency components.	31
4.10	FAN layer architecture. [29]	32
5.1	Complete methodology for epilepsy detection.	37
5.2	EEG Signal Segmentation with 5s Window and 50% Overlap.	38
5.3	ConvNext-BiLSTM Network Augmented with Attention Mechanisms.	39
5.4	Complete B-GFAN methodology with multi-modal attention and uncertainty quantification for epileptic seizure detection.	41
5.5	Multi-scale STFT decomposition with spectral attention and uncertainty propagation.	42
6.1	ConvNext-BiLSTM model training and validation metrics.	50
6.2	Accuracy in LOSO Experiment (ConvNext-BiLSTM Network).	51
6.3	ROC Curve LOSO Fold1 (ConvNext-BiLSTM Network).	51
6.4	Confusion Matrix LOSO Fold1 (ConvNext-BiLSTM Network).	52
6.5	Two-dimensional t-SNE visualization of the features at the output layer of (a) BiLSTM, (b) Multi-Head Self Attention.	52
6.6	Two-dimensional t-SNE visualization of the features at the output layer of (a) ConvNext Backbone , (b) SE Block Attention.	53
6.7	B-GFAN model training progression showing accuracy and loss evolution.	54
6.8	Detailed loss progression analysis for B-GFAN training.	54
6.9	Precision and recall progression for B-GFAN model training.	55
6.10	F1-score analysis showing performance consistency and variance across validation folds.	55

6.11	Cross-validation performance comparison across different folds for B-GFAN model.	56
6.12	Enhanced loss progression with uncertainty bands showing training stability. The uncertainty bands (± 1) indicate consistent learning across different random initializations, with minimal generalization gap between training and validation losses, demonstrating robust model training without overfitting.	56
6.13	Cross-validation robustness analysis showing consistent performance across all folds.	57
6.14	Precision-recall balance and final loss consistency analysis across validation folds.	57
6.15	Distribution of best performance metrics (F1-Score, Accuracy, AUC-ROC) across all folds, showing tight clustering around high performance values with minimal variance, indicating exceptional model stability.	58
6.16	Model stability and training efficiency analysis across validation folds.	58
6.17	Metric correlation matrix showing strong positive correlations between accuracy, F1-score, and precision (0.82-0.99), with expected negative correlation with recall (-0.73 to -0.75), indicating balanced optimization across metrics without overfitting to any single measure.	59
6.18	Smoothed loss progression with generalization gap analysis. The minimal gap between training and validation losses throughout training indicates excellent generalization without overfitting, while the smooth convergence demonstrates stable optimization dynamics.	60
6.19	Comprehensive performance summary and trend analysis for B-GFAN model.	60
6.20	Model stability analysis across final training epochs showing exceptional stability (mean: 0.993 ± 0.004) across all folds, indicating highly reliable and consistent model behavior suitable for clinical deployment.	61
6.21	Cross-validation summary statistics table providing comprehensive overview of model performance consistency. All folds achieve optimal performance at epoch 15 with minimal variance (F1-Score: 0.938 ± 0.003 , Accuracy: 0.957 ± 0.003), demonstrating exceptional reproducibility and reliability.	61
6.22	Confusion matrix analysis showing excellent classification performance with 99.0% true negative rate and 94.3% true positive rate. The low false positive rate (1.0%) and false negative rate (5.7%) indicate clinically acceptable performance for seizure detection applications.	62

6.23	Receiver Operating Characteristic (ROC) curve demonstrating excellent discriminative ability with AUC = 0.970. The curve shows superior performance compared to random classification, with optimal threshold ($J = 0.934$) providing excellent balance between sensitivity and specificity.	62
6.24	Precision-recall performance and threshold optimization analysis.	63
6.25	Classification results breakdown showing the distribution of predictions: 87.1% true negatives, 11.4% true positives, 0.8% false positives, and 0.7% false negatives, demonstrating the model's ability to handle class imbalance effectively.	63
6.26	Probability calibration curve showing excellent calibration properties. The B-GFAN model (orange line) closely follows the perfect calibration line (black dotted), indicating that predicted probabilities accurately reflect true likelihood of seizure occurrence, essential for clinical confidence in predictions.	64
6.27	Simplified performance summary across all folds showing consistent high performance in both F1-Score (ranging 0.934-0.941) and Accuracy (ranging 0.953-0.960), with minimal inter-fold variation demonstrating excellent generalization capability.	64

CHAPTER I

Work Distribution

Table 1.1: Work Distribution between Group Members

Maimuna Chowdhury (ConvNext-BiLSTM Network Enhanced with Attention Mechanisms)	Kazi Fahim Tahmid (Bayesian-Graph Fourier Analysis Network with Uncertainty Quantification)
1.Dual-domain dual-path design- designing the ConvNext-BiLSTM two-path structure enabling effective parallel processing of both raw EEG signals and their time-frequency representations.	1.B-GFAN Mathematical Framework- developing the theoretical foundation integrating spectral graph theory, Fourier analysis networks, and Bayesian neural networks with comprehensive uncertainty quantification mechanisms.
2.Spatial Attention- Implementing the SE Block attention, which consists of channel attention mechanisms to enhance spatial feature extraction from EEG scalogram.	2. Multi-Modal Attention Architecture- implementing four specialized attention mechanisms (spatial, spectral, graph, and cross-modal attention) for enhanced feature selection and clinical interpretability.
3.Multi-head Self Attention- Implementing a multi-head attention module applied on the bidirectional LSTM outputs from raw EEG signals, enabling the model to learn complex temporal features.	3.Graph Spectral Processing- designing graph construction frameworks with graph attention networks, Laplacian eigendecomposition, and spectral filtering for electrode connectivity modeling and seizure propagation analysis.
4.Experiments & ablations- Conducting experiments and ablation studies on the ConvNext-BiLSTM and attention enhanced ConvNext-BiLSTM to demonstrate the advantages of the attention enhanced approach.	4. Uncertainty Quantification & Clinical Deployment- implementing probabilistic inference, Monte Carlo dropout variants, attention-aware curriculum learning, and comprehensive evaluation protocols for clinical reliability assessment.

CHAPTER II

Introduction

2.1 Background

Epilepsy is one of the most common neurological disorders, affecting millions of people globally. It is characterized by recurrent, unprovoked seizures caused by abnormal electrical discharges in the brain. An effective and timely diagnosis of epilepsy is crucial for managing the condition. However, one of the primary challenges in automatic detection of epilepsy is the scarcity of labeled data, especially EEG data. The electroencephalogram (EEG) is a critical tool in monitoring electrical brain activity and detecting epileptic episodes. Recent advancements in deep learning and signal processing techniques have enabled more effective analysis of EEG signals for detecting abnormal patterns related to epilepsy.

2.2 Problem Statement

Accurate detection of epileptic events using EEG signals remains challenging due to the highly variable and noisy nature of EEG data. Traditional methods often struggle to extract meaningful patterns from such complex signals. To address these challenges, this work proposes two complementary solutions: a hybrid deep learning model combining ConvNext, BiLSTM, and attention mechanisms for effective spatial and temporal feature extraction, and a novel Bayesian-Graph Fourier Analysis Network (B-GFAN) that leverages graph spectral theory, Fourier analysis, and Bayesian uncertainty quantification to capture seizure-relevant connectivity and frequency patterns with clinical reliability.

2.3 Objectives

The main objectives of this research are as follows:

1. To develop a robust and real-time system for accurate detection of epileptic seizures using EEG signals, ensuring reliability and timely identification of seizure events.
2. To apply efficient data preprocessing methods that enable informative feature extraction for improved model performance.
3. To design and develop lightweight, computationally efficient models for epileptic seizure detection.

4. To validate the proposed system through comprehensive performance comparison with existing methods on the CHB-MIT EEG dataset.

2.4 Scope

This thesis focuses on automated epileptic seizure detection using scalp EEG signals. Although EEG analysis spans various clinical and research applications, the scope of this work is strictly limited to supervised learning methods applied to the CHB-MIT scalp EEG dataset. The primary goal is to develop and compare two novel architectures—(1) a ConvNext-BiLSTM model enhanced with attention mechanisms and (2) a Bayesian-Graph Fourier Analysis Network (B-GFAN) with uncertainty quantification—to improve detection accuracy, reliability, and interpretability.

2.4.1 Signal Processing Frameworks and Tools

All implementations are performed in **Python** using **PyTorch** for neural network development and **Pyro** for Bayesian inference. EEG preprocessing leverages **MNE-Python** for filtering, artifact removal, and segmentation. Data handling and numerical operations use **NumPy** and **SciPy**, while **Matplotlib** and **Seaborn** support visualization of signals, attention maps, and uncertainty estimates. Experiment tracking is managed via **Weights & Biases (W&B)**.

2.4.2 Dataset

The publicly available **CHB-MIT scalp EEG Dataset** comprising 23 pediatric subjects and 198 seizure recordings is used for training and evaluation. Signals are bandpass-filtered (0.5–70Hz), segmented into 5s windows with 50% overlap, and labeled per seizure occurrence. Leave-One-Subject-Out (LOSO) cross-validation ensures subject-independent performance assessment.

2.4.3 Model Architectures

The research develops two complementary models:

1. **Attention Enhanced ConvNext-BiLSTM Dual Branch Network:** A dual-path design where a 2D-CNN processes time–frequency scalograms and a BiLSTM captures raw temporal sequences. Separate spatial and temporal attention modules enhance feature selection before fusion.
2. **Bayesian-Graph Fourier Analysis Network (B-GFAN):** A lightweight graph-spectral architecture integrating Fourier Analysis Networks with graph

attention layers. Multi-modal attention (spatial, spectral, graph, cross-modal) and Bayesian layers provide uncertainty estimates.

2.4.4 Training Details

Both models are trained with the **AdamW** optimizer (learning rate 1×10^{-4} , $\beta_1 = 0.9$, $\beta_2 = 0.999$) and **Cosine Annealing** scheduler. Training runs for **100 epochs** per LOSO split with early stopping on validation F1-score. Data augmentation includes random Gaussian noise injection and time-stretching. Bayesian layers use Monte Carlo Dropout ($p = 0.2$) for epistemic uncertainty estimation.

2.4.5 Evaluation Metrics

Performance is measured using:

- **Sensitivity (Recall)** and **Specificity**
- **F1-Score** for balanced detection accuracy
- **False Positive Rate** (false alarms per hour)
- **Detection Latency** (time from electrographic onset to detection)
- **Expected Calibration Error (ECE)** and **Brier Score** for uncertainty calibration

2.4.6 Computational Resources

Experiments are conducted on an **NVIDIA RTX 3090 GPU** (24GB) with **CUDA** and **cuDNN** support. Batch processing and mixed-precision training are employed to maximize throughput. Logs and attention/uncertainty visualizations are recorded via **TensorBoard** and **W&B**.

2.4.7 Limitations of the Scope

This study is constrained to:

- **Scalp EEG only**; intracranial EEG or other modalities are excluded.
- **Single-dataset evaluation** on CHB-MIT; cross-database generalization is not assessed.
- **Supervised learning**; unsupervised or semi-supervised methods are out of scope.
- **Fixed window size** (5s) and overlap; variable segmentation strategies are not explored.

- **Standard preprocessing:** advanced artifact correction techniques (e.g., ICA ensemble) are not implemented.

These limitations maintain focus on rigorous comparison between the ConvNext-BiLSTM and B-GFAN approaches under consistent conditions.

2.5 Unfamiliarity of the Problem

Accurate epileptic seizure detection from scalp EEG signals remains unfamiliar and challenging due to:

- **High variability and non-stationarity:** EEG waveforms exhibit rapid, patient-specific fluctuations, making consistent feature extraction difficult.
- **Scarcity and imbalance of labeled data:** Limited seizure events and uneven class distributions hinder robust model training and risk overfitting.
- **Complex spatial-spectral relationships:** Seizure signatures manifest as both localized network interactions and frequency-specific patterns that are hard to model jointly.
- **Ambiguity in seizure boundaries:** Gradual onset and offset of epileptic activity introduce label uncertainty at window edges.
- **Clinical deployment constraints:** Real-time requirements, artifact contamination, and inter-subject variability limit generalization across patients and recording conditions.

2.6 Project Planning

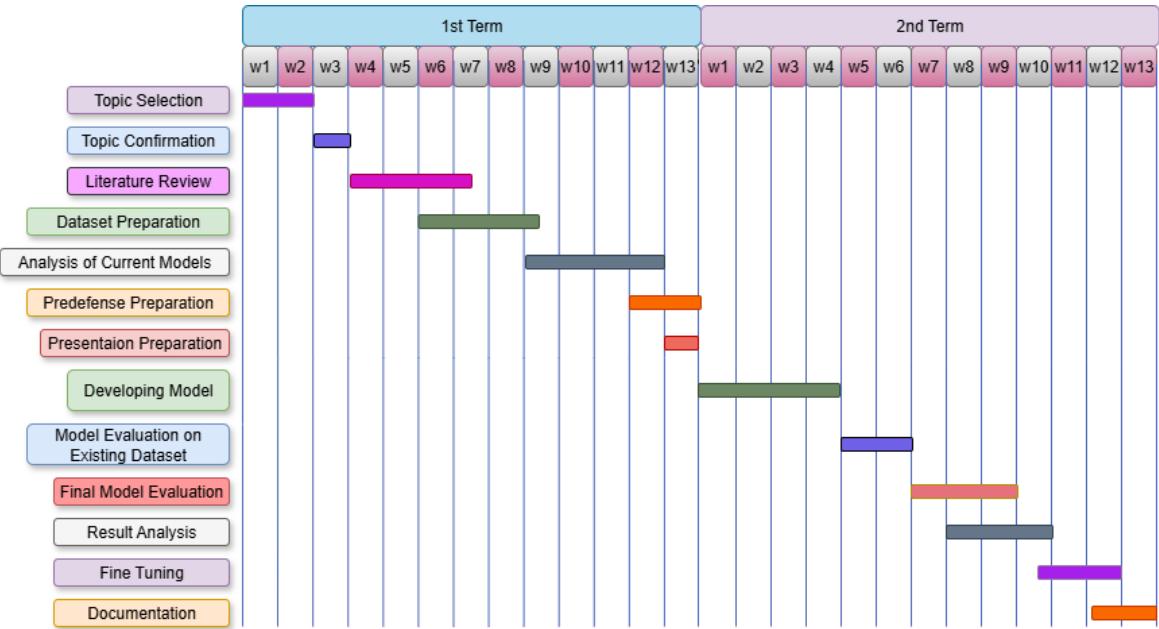


Figure 2.1: A preliminary timeline of the thesis.

2.7 Financial Analyses and Budget

This project minimized direct expenses by utilizing institutional resources:

- **Hardware.** Access to A6000 GPUs (market price \$10k–\$15k each, not purchased for this work).
- **Software.** Open-source stack: PyTorch, CUDA (no license fees).
- **Storage.** ~1 TB for datasets, logs, and checkpoints.

A detailed, itemized budget (if required) can be included in an appendix; the main cost driver is compute access.

2.8 Applications

The applications of Epileptic Seizure Detection Systems span various fields, such as:

- **Clinical diagnosis and monitoring:** Automated seizure detection can help reduce manual labor of EEG analysis and can support long-term patient monitoring in different settings.
- **Real-time seizure prediction and alerts:** Provides timely warnings to patients and caregivers, which helps to prevent injuries during seizures.

- **Personalized treatment management:** Helps by providing accurate seizure data to tailor medications and therapies for individual patients.
- **Research and drug development:** Automated systems provide large-scale, accurate seizure data collection, facilitating neurological research and accelerating development of new anti epileptic treatments.

2.9 Organization of Report

The purpose of this section is to provide readers with a clear understanding of the order in which information is presented and to assist them in navigating the document. The thesis consists of the following chapters:

- **Chapter I:** Provides the work distribution of the thesis which is done by a group of two members.
- **Chapter II:** Introduces the clinical and signal-processing background of epileptic seizure detection using EEG. Covers EEG fundamentals, CHB-MIT dataset characteristics, preprocessing challenges, and the motivation for developing robust, uncertainty-aware detection methods.
- **Chapter III:** Reviews existing EEG-based seizure detection techniques, including conventional feature-engineering approaches, CNN- and RNN-based models, attention-enhanced architectures, and graph-spectral methods. Concludes with a comparative analysis highlighting gaps in uncertainty quantification and interpretability.
- **Chapter IV:** Details the proposed dual-method framework for seizure detection. Describes the ConvNext-BiLSTM with spatial and temporal attention modules alongside the Bayesian-Graph Fourier Analysis Network (B-GFAN), including graph construction, Fourier decomposition, multi-modal attention, and Bayesian inference foundations.
- **Chapter V:** Provides the technical details necessary to reproduce and implement the proposed approach. It covers the experimental setup, evaluation metrics, implementation and results, objectives achieved and financial analyses. Hardware and software environments used in the experiments are also described. In addition, the chapter details how different components of the proposed architecture were integrated and fine-tuned to achieve the reported performance.
- **Chapter VI:** Explores the wider implications of the research in relation to societal, health, environmental, safety, ethical, legal, and cultural aspects. It examines potential

risks and challenges that may arise from applying the research findings and further discusses the ethical responsibilities and cultural considerations associated with their implementation.

- **Chapter VII:** Discusses the complex engineering challenges encountered in the research and the strategies employed to address them. It emphasizes the innovative methods or solutions developed and highlights the contribution of this work to advancing the field of engineering.
- **Chapter VII:** Concludes the thesis by summarizing the key findings, revisiting the research objectives, and reflecting on their implications for theory and practice. This chapter also outlines future research directions, encouraging further exploration in the domain of high-quality and efficient image super-resolution.

2.10 Summary

In summary, automated epileptic seizure detection from scalp EEG signals presents a critical yet challenging problem due to high signal variability, limited labeled data, and ambiguous seizure boundaries. Traditional feature-based and deep learning methods have advanced detection accuracy: CNN- and RNN-based architectures extract spatial and temporal patterns; attention mechanisms highlight salient EEG features; graph-based models capture electrode connectivity; and Bayesian networks provide uncertainty estimates. However, these approaches often face limitations such as overfitting to specific patients, lack of calibrated confidence, and difficulty in interpreting model decisions. To address these challenges, this work proposes a dual-methodology framework that combines a ConvNext-BiLSTM model with spatial, temporal, and cross-modal attention and a Bayesian-Graph Fourier Analysis Network (B-GFAN) integrating spectral graph theory, Fourier decomposition, and uncertainty quantification. This hybrid design aims to deliver robust, interpretable, and clinically reliable seizure detection across diverse patient populations and recording conditions.

CHAPTER III

Literature Review

3.1 Introduction

Automated epileptic seizure detection from scalp EEG signals is a critical task in clinical neuroengineering, aiming to identify seizure events from continuous multichannel recordings. This problem is inherently challenging due to the non-stationary, noisy, and patient-specific nature of EEG data. Over the years, a wide range of methods has been developed to address seizure detection. Early work relied on handcrafted features—spectral power, wavelet coefficients, and nonlinear dynamics—combined with classical classifiers. The advent of deep learning introduced CNN and RNN architectures that automatically learn spatial and temporal patterns from raw or transformed EEG segments. Attention mechanisms further improved performance by adaptively focusing on informative channels and time points. Graph-based approaches incorporated electrode connectivity through spectral graph transforms and graph attention networks, capturing spatial relationships across the scalp. Bayesian neural networks and uncertainty quantification techniques added calibrated confidence estimates, addressing the clinical need for reliable decision support. More recently, hybrid frameworks have emerged that fuse multiple modalities—temporal signals, time–frequency representations, and graph spectral features—within unified architectures. These advances underscore the importance of balancing detection accuracy, interpretability, and clinical reliability. A systematic literature review is therefore essential to analyze existing methods, highlight their strengths and limitations, and identify open challenges in EEG-based seizure detection. This chapter synthesizes contributions across feature-engineering, deep learning, attention mechanisms, graph-spectral models, and Bayesian inference, providing a comprehensive foundation for the dual-methodology framework proposed in this work.

3.2 Relevant Terminology

- **EEG (Electroencephalogram)** – Non-invasive recording of electrical brain activity via scalp electrodes.
- **CHB-MIT Dataset** – Publicly available pediatric scalp EEG database with 23 subjects and annotated seizure events.

- **CNN (Convolutional Neural Network)** – Deep architecture for spatial feature extraction from EEG scalograms or raw signals.
- **BiLSTM (Bidirectional Long Short-Term Memory)** – Recurrent network capturing forward and backward temporal dependencies in EEG time series.
- **Attention Mechanism** – Module that adaptively weights spatial, spectral, graph, or cross-modal features based on relevance.
- **Spectral Graph Theory** – Mathematical framework using graph Laplacian eigenmodes to model electrode connectivity and signal propagation.
- **Graph Laplacian** – Matrix $\mathcal{L} = I - D^{-1/2} W D^{-1/2}$ whose eigenvectors define spatial modes of EEG electrode network.
- **Fourier Analysis Networks (FAN)** – Layers that decompose periodic and non-periodic components via learnable Fourier bases with spectral attention.
- **Bayesian Neural Network** – Probabilistic model placing distributions over weights and parameters to quantify epistemic uncertainty.
- **Aleatoric Uncertainty** – Data-inherent noise arising from measurement variability and ambiguous seizure annotations.
- **Epistemic Uncertainty** – Model-based uncertainty due to parameter estimation and limited training data, estimated via Monte Carlo dropout.
- **B-GFAN (Bayesian-Graph Fourier Analysis Network)** – Lightweight architecture integrating FAN, graph spectral filtering, multi-modal attention, and Bayesian inference.
- **LOSO (Leave-One-Subject-Out)** – Cross-validation protocol holding out each subject in turn to assess model generalization across individuals.
- **STFT (Short-Time Fourier Transform)** – Time-frequency analysis tool using fixed-window Fourier decomposition with optional uncertainty perturbations.
- **CWT (Continuous Wavelet Transform)** – Time-frequency method with variable window sizes for multi-scale analysis of non-stationary EEG.
- **ICA (Independent Component Analysis)** – Blind source separation technique for artifact removal, often ensemble-averaged for uncertainty estimation.
- **Monte Carlo Dropout** – Technique approximating Bayesian inference by applying dropout at inference to obtain uncertainty estimates.

3.3 Related Works

Much research has been performed over the years to solve the challenges of automated epileptic seizure detection using scalp EEG signals. Common approaches include using Convolutional Neural Networks, Graph Neural Networks, and Fourier-based methods. Every method has its advantages and disadvantages. Some of the prominent work studied is mentioned below.

3.3.1 CNN-LSTM based Methods

During a seizure, the EEG of epileptic patients exhibits distinct epilepsy-related discharges, including spikes, sharp waves, and sharp-slow waves, although these patterns can differ across various channels. Thus, identifying and extracting appropriate features is crucial for effective epilepsy detection. Recent advancements in machine learning and deep learning have paved the way for the development of automated epilepsy detection systems. These systems aim to capture both spatial and temporal patterns in EEG signals, leveraging models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks.

In the work by [1], a CNN-based architecture was used for the detection of drug-resistant epilepsy, highlighting the effectiveness of CNNs in extracting spatial features from EEG signals. This study emphasized the importance of leveraging CNNs to improve the accuracy of seizure detection, especially when paired with recurrent networks such as LSTMs for capturing temporal dependencies.

In addition to CNNs, LSTMs have been widely used to capture the temporal dynamics of EEG signals. [2] proposed using a ResNet-LSTM combination, which enhanced the model's capacity to extract spatial features by dynamically screening EEG channels using RCMDE while preserving temporal dependencies using LSTM, improving overall classification accuracy.

Similarly, [3] proposed classification of self-limited epilepsy using machine learning model Random Forest and deep learning model Resnet for diagnosing patients with central temporal spikes.

Wavelet transforms have also been widely explored as a feature extraction method for epilepsy detection. In [4], the authors proposed a wavelet-based method to analyze EEG signals, which allowed for effective decomposition of the signal into different frequency bands. The combination of wavelet transforms with CNNs has shown to significantly improve detection accuracy, especially for signals with high-frequency components.

In addition to traditional machine learning methods, multimodal approaches have gained significance as a means of enhancing seizure detection by integrating different types of data. In [5], a CNN-LSTM hybrid model was introduced which leverages both time series window

and time-frequency representation, which demonstrated strong performance in classifying seizure events by combining the strengths of both architectures. In [6], the authors proposed converting EEG signals into image representations of different window lengths highlighting the significance of selecting an appropriate window length for precise seizure detection.

Several studies have focused on improving classification accuracy through advanced pre-processing techniques. In [7], a multi-scale dilation-based convolutional neural network was introduced, which allowed the model to analyze both short and long-term dependencies in the EEG signals. The use of dilation techniques expanded the receptive field of the network, enabling it to capture important features that occur over different time scales.

Another major challenge in epilepsy detection is the need for real-time analysis and low-latency predictions. In [8], a hybrid model combining Short-Time Fourier Transform (STFT) and GoogleNet was developed, where the addition of attention mechanisms allowed the model to prioritize significant channels in the EEG signals, leading to improved accuracy in real-time seizure detection.

Attention-based modeling has been a focus of several recent studies. In [9], the authors proposed a new type of CNN architecture named ConvNeXt which is a hybrid of vision transformers and ResNet. This provides the more simplicity of CNN and also integrates the sharp features of vision transformers. In [10] the authors explored the use of 3D-CNN in conjunction with self attention mechanism to effectively detect seizures. By incorporating self attention into the classification process, the model could account for variability in the EEG data and provide more robust predictions. This approach aligns with the overall goal of this thesis, which seeks to use attention-aware fusion techniques to improve the reliability of epilepsy detection systems.

In summary, the literature reflects a growing trend toward using deep learning techniques such as CNNs, LSTMs, and attention mechanisms for epilepsy detection. These models are increasingly being combined with multimodal data fusion, wavelet-based feature extraction to improve performance. Table 3.1 summarizes the CNN based methods.

3.3.2 Graph Neural Network-based Methods

Recent advances in graph neural networks have shown significant promise in epileptic seizure detection by modeling the spatial relationships between EEG electrodes and capturing brain connectivity patterns during seizure events.

In 2020, Li *et al.* proposed a Graph-Generative Neural Network (GGN) model for dynamic discovery of brain functional connectivity via deep analysis of scalp EEG signals. The GGN model generates brain functional connectivity graphs to extract spatial-temporal resolution of various onset epilepsy seizure patterns. Their supervised GGN model achieved 91% accuracy in classifying seven types of epileptic seizure attacks, outperforming CNN (65%), standard GNN (74%), and Transformer (82%) architectures on a clinically proven dataset

of over 3,047 epileptic seizure cases [11]. While Lian *et al.* developed an efficient Graph Convolutional Network (GCN) model architecture for seizure prediction using scalp EEG data. Their approach employs global-local graph convolutional neural networks in a data-driven way to jointly learn graph structure and link weights during task-related learning of EEG signals. The experimental results demonstrated superior performance compared to conventional CNN and standard GCNN models [12].

In 2021, Zhao *et al.* focused on learning spatial connectivity of the brain to distinguish between seizure and non-seizure phases using an optimized Graph Attention Network (GAT). Their model achieved exceptional performance with 98.33% sensitivity on the CHB-MIT dataset by adaptively learning electrode connectivity patterns and emphasizing seizure-relevant spatial relationships [13].

In 2024, Hajisafi *et al.* introduced NeuroGNN, a dynamic Graph Neural Network framework that captures the dynamic interplay between EEG electrode locations and the semantics of their corresponding brain regions. The approach constructs multi-context correlations characterized by spatial proximity, temporal dependencies, semantic similarities, and taxonomic correlations across brain regions. NeuroGNN significantly outperformed existing state-of-the-art models in both seizure detection and classification tasks [14]. Li *et al.* proposed a dynamical graph neural network with attention mechanism for single-channel EEG signals. Their approach employs Empirical Mode Decomposition (EMD) to construct graphs and obtains optimal adjacency matrices through model optimization. The multilayer dynamic graph neural network with attention mechanism achieved remarkable results with 99.83% accuracy across 12 classification tasks on the University of Bonn epileptic EEG database [15].

In 2025, Amir *et al.* presented a dual-task Graph Neural Network framework that operates on windowed stereo-EEG (sEEG) recordings to jointly predict seizure-freedom outcomes and identify seizure-onset-zone (SOZ) channels. Their approach leverages rich node features including spectral, statistical, wavelet, Hjorth, and local graph features, demonstrating the effectiveness of GNN-based modeling for surgical planning in drug-resistant epilepsy [16]. Mazurek *et al.* employed attention-based Graph Neural Networks to process EEG signals represented as graphs for automatic epilepsy detection using accessible hardware in low-resource settings. Their adapted GAT architecture analyzes edges rather than nodes to emphasize connectivity biomarkers, achieving promising classification performance while highlighting specific fronto-temporal region connections [17]. Moreover, Yan *et al.* proposed a Dynamic Temporal-Spatial Graph Attention Network (DTS-GAN) to address limitations of fixed-topology graph models in analyzing time-varying brain networks. By integrating graph signal processing with hybrid deep learning, DTS-GAN achieved 89-91% accuracy and weighted F1-score of 87-91% in classifying seven seizure types on the TUSZ dataset, significantly outperforming baseline

models [18]. Xiang *et al.* developed a synchronization-based graph spatio-temporal attention network for seizure prediction. Their approach models phase synchronization information of full-lead EEG signals as graph structure and extracts spatial information using GAT while capturing temporal features with Transformer models, demonstrating improved prediction results for focused subjects [19]. On the other hand, Tian *et al.* introduced EEG-GCA (EEG-based epilepsy detection with Graph Correlation Analysis), an unsupervised graph-based model that detects abnormal channels and segments based on inter-channel correlation analysis. The method employs weight-sharing GNN with KL divergence regularization and uniquely requires no access to seizure data during training, outperforming all relevant supervised methods [20].

3.3.3 Fourier-based Methods

Fourier analysis and spectral decomposition techniques have emerged as powerful tools for epileptic seizure detection by capturing frequency-domain characteristics and spectral patterns that distinguish seizure from non-seizure states.

In 2008, Ghosh *et al.* demonstrated the effectiveness of Fourier Transform (FT) and PCA-based feature extraction in improving deep learning performance for seizure detection in patients with disabilities. Their study emphasizes the critical role of spectral feature extraction in enhancing model robustness and clinical applicability [21].

In 2021, Mehla *et al.* introduced a novel approach for epileptic seizure identification using Fourier Decomposition Method (FDM). The EEG signals are decomposed into Fourier Intrinsic Band Functions (FIBFs), and features are extracted using position, velocity, and acceleration concepts with L_p norms. Their method achieved exceptional classification accuracy of 99.96% on the BONN dataset and 99.94% on the CHB-MIT dataset using computationally efficient Fast Fourier Transform (FFT) algorithms [22].

In 2022, Peng *et al.* employed Short-Time Fourier Transform (STFT) for seizure prediction using domain adaptation techniques. The STFT extracts time-frequency features from raw EEG data, and an autoencoder maps these features into high-dimensional space. By minimizing inter-domain distance in the embedding space, their model learns domain-invariant information and improves generalization ability across different patients [23]. Godoy *et al.* developed Temporal Multi-Channel Transformers (TMC-T and TMC-ViT) for EEG-based epileptic seizure prediction. While primarily transformer-based, their architecture incorporates Fourier analysis for preprocessing and feature enhancement, achieving superior performance compared to CNN, LSTM, and hybrid CNN-BiLSTM approaches on the CHB-MIT dataset [24].

In 2024, Shen *et al.* presented a real-time epilepsy seizure detection approach combining STFT with GoogleNet CNN architecture. The STFT transforms EEG signals into time-frequency representations that capture both temporal and spectral characteristics

crucial for accurate seizure detection, demonstrating computational efficiency suitable for real-time applications [8].

In 2025, an advanced temporal graph attention model was introduced by Zhang *et al.*, which constructs dynamic EEG graphs capturing both spatial electrode interactions and temporal dependencies. By applying joint node-time attention mechanisms, the model effectively identifies localized abnormal patterns and propagation dynamics, enhancing seizure and anomaly detection capabilities. Evaluated on the TUH Abnormal EEG dataset, the approach demonstrated superior accuracy, sensitivity, and specificity compared to existing methods, showcasing robust performance across varying window sizes and channel counts. This work validates the importance of modeling spatiotemporal EEG interactions through graph attention networks, aligning with the framework adopted in this thesis for reliable epileptic seizure detection. [25] Nath *et al.* investigated high-frequency EEG activities in the gamma band (40–100 Hz) using Welch’s spectral analysis and phase space reconstruction. Their method extracted spectral and nonlinear features to distinguish epileptic from normal EEG signals. Evaluated on the Bonn dataset, it achieved around 94–95% classification accuracy, demonstrating the effectiveness of integrating Fourier-based spectral analysis with dynamical system techniques for seizure detection. [26] While Chopannavaz *et al.* proposed reconstruction-based models for seizure prediction using Short-Time Fourier Transform (STFT) applied to ECG signals. Their approach employs STFT for feature extraction combined with autoencoder architectures, demonstrating the effectiveness of Fourier-based methods beyond traditional EEG analysis [27].

Table 3.1: A brief summary of CNN-LSTM based methods for epilepsy detection using EEG signals

Paper	Techniques	Dataset	Performance Measure	Weakness/Remarks
Yang et al. [1]	CNN for drug-resistant epilepsy detection	CHB-MIT	High accuracy for detecting drug-resistant epilepsy	Limited to specific epilepsy cases.
Fredes et al. [4]	Wavelet transform for feature extraction	CHB-MIT	Effective frequency band decomposition	Limited data quality and suboptimal SVM tuning opportunities.
Abdulwahhab et al. [5]	CNN-LSTM hybrid model for capturing spatial-temporal dependencies	Bonn EEG Dataset	Improved classification of seizure events	Evaluation does not include unseen patient data.
Song et al. [2].	ResNet-LSTM hybrid model for epilepsy detection	Temple University EEG Corpus	High accuracy with robust temporal feature extraction	Requires careful channel screening.
Tasci et al. [28]	Curated dataset based classification leveraging ResNet	Custom Dataset	Enhanced performance in detection of seizures with central temporal spikes	Limited to specific epilepsy patients.
Assim et al. [6]	Conversion of EEG signals to image representations for CNN-based analysis	Custom dataset	Improved spatial pattern recognition from EEG signals with varying window lengths	Lacks validation of performance in real-world settings.
Shen et al. [8]	Short-time Fourier Transform (STFT) combined with GoogleNet	CHB-MIT	Real-time seizure detection with attention mechanism	Struggles to detect seizures characterized by amplitude depression.
Karanti et al. [7]	Multi-scale dilation-based CNN for multi-resolution analysis	Freiburg EEG Dataset	Improved detection across different temporal resolutions	High computational complexity.
Khan et al. [10]	Attention Enhanced 3D-CNN for capturing spatial-temporal dependencies	CHB-MIT, TUH	Robust and Generalized Classification	Needs to optimize computational efficiency.

Table 3.2: Comparative analysis of Graph Neural Network-based methods for epileptic seizure detection

Methods	Approach	Advantages	Disadvantages
Graph Neural Network-Based Methods	1. Graph-Generative Neural Networks (GGN) for dynamic brain connectivity discovery [11].	1. Excellent modeling of spatial electrode relationships and brain connectivity patterns [11, 13].	1. High computational complexity due to graph operations and attention mechanisms [14, 18].
Continued on next page			

Table 3.2 – continued from previous page

Methods	Approach	Advantages	Disadvantages
	2. Global-local G-CNN with joint structure and weight learning [12]. 3. GAT for spatial connectivity optimization [13]. 4. Dynamic GNN frameworks with multi-context correlations and attention mechanisms [14, 15]. 5. Dual-task GNN for seizure-onset-zone identification using sEEG [16]. 6. Temporal-spatial graph attention networks with synchronization modeling [18, 19].	2. High classification accuracy (91-99.83%) across multiple seizure types and datasets [11, 15]. 3. Superior performance compared to CNN, standard GNN, and Transformer architectures [11]. 4. Effective capture of dynamic temporal-spatial brain network changes [14, 18]. 5. Unsupervised approaches eliminate need for seizure data during training [20]. 6. Suitable for low-resource clinical settings with accessible hardware [17].	2. Requires careful graph construction and adjacency matrix optimization [12, 15]. 3. Performance highly dependent on electrode placement accuracy and connectivity assumptions [13]. 4. Limited generalization across different EEG recording systems and electrode configurations [17]. 5. Complex architecture design increases training time and hyperparameter tuning difficulty [14, 19]. 6. May struggle with single-channel or limited electrode setups [15].

Continued on next page

Table 3.2 – continued from previous page

Methods	Approach	Advantages	Disadvantages
	7. Unsupervised graph correlation analysis with weight-sharing GNN [20].		

Table 3.3: Comparative analysis of Fourier-based methods for epileptic seizure detection

Methods	Approach	Advantages	Disadvantages
Fourier-Based Methods	<p>1. Fourier Decomposition Method (FDM) with Fourier Intrinsic Band Functions and L_p norms [22].</p> <p>2. Short-Time Fourier Transform (STFT) with domain adaptation techniques [23].</p> <p>3. Multi-channel Transformers with Fourier preprocessing and feature enhancement [24].</p> <p>4. Real-time STFT combined with GoogleNet CNN architecture [8].</p>	<p>1. Exceptional classification accuracy (99.94-99.96%) on standard datasets [22].</p> <p>2. Computationally efficient using Fast Fourier Transform (FFT) algorithms [22].</p> <p>3. Effective capture of time-frequency characteristics crucial for seizure detection [23, 8].</p> <p>4. Superior cross-patient generalization through domain-invariant feature learning [23].</p>	<p>1. Sensitive to window size selection in STFT, affecting time-frequency resolution trade-offs [23, 8].</p> <p>2. May lose temporal locality information during frequency domain transformation [22].</p> <p>3. Performance degrades with non-stationary EEG signals and artifacts [26].</p> <p>4. Requires careful parameter tuning for optimal frequency band selection [26].</p>

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Table 3.3 – continued from previous page

Methods	Approach	Advantages	Disadvantages
	5. High-frequency gamma band analysis using Welch's spectral method and phase space reconstruction [26]. 6. Temporal graph attention with joint spectral-spatial feature extraction [25].	5. Real-time processing capability suitable for clinical monitoring [8]. 6. Robust identification of high-frequency seizure biomarkers (40-100 Hz gamma band) [26].	5. Limited effectiveness on single-channel EEG compared to multi-channel approaches [25]. 6. Computational overhead increases with higher frequency resolution requirements [27].

CHAPTER IV

Background Analysis

This chapter provides an overview of theoretical methods and techniques relevant to our research. We will discuss useful methods for EEG signal processing, data augmentation, and neural networks, which will serve as the foundation for further work described in the implementation phase.

4.1 Preprocessing Techniques for EEG Data

Electroencephalography (EEG) is a non-invasive method used to record the brain's electrical activity through electrodes placed on the scalp. EEG captures the spontaneous electrical impulses generated by neuronal activity in the brain, primarily from the cerebral cortex. These signals reflect the dynamic brain function and are represented as waveforms with different frequency bands, such as alpha, beta, delta, and theta waves.

EEG signals play a crucial role in detecting epileptic seizures because seizures cause abnormal, sudden electrical discharges in the brain. By analyzing EEG patterns, clinicians and automated systems can identify the onset and progression of seizure activity.

Inherently, EEG signals are noisy and non-stationary, making preprocessing essential to extract meaningful features. Below, we discuss some well-established preprocessing techniques for EEG data.

4.1.1 Butterworth Bandpass Filter

The Butterworth bandpass filter plays a significant role in EEG signal analysis for removing unwanted frequencies while preserving important brain signal components. With a smooth frequency response, this filter effectively eliminates slow drifts and high-frequency noise, such as muscle artifacts and electrical interference, enhancing signal quality for accurate seizure detection.

4.1.2 EEG Signal Segmentation

EEG signal segmentation divides continuous EEG recordings into shorter and more stable EEG segments to overcome the inherently non-stationary nature of EEG signals. The quasi-stationary segments allow for more accurate and consistent feature extraction. Also, segmentation increases the number of training samples and reduces boundary effects,

which together enhance the sensitivity and robustness of models in detecting brain activities such as epileptic seizures.

4.1.3 EEG Data Augmentation

Data augmentation techniques help the model to learn invariant and diverse feature representations, reducing overfitting and enhancing detection accuracy. In this study, multiple EEG-specific augmentation techniques have been employed, including:

Gaussian Noise Injection: Addition of physiologically plausible noise to mimic sensor variability.

Time Warping: Adjustment of temporal dynamics with seizure-awareness to preserve critical seizure morphology.

Amplitude Scaling: Simulation of signal gain fluctuations within realistic ranges.

4.1.4 Z-Score Normalization

Z-score normalization is a common and widely used data preprocessing technique. It standardizes segments by transforming them to have a mean of zero and a standard deviation of one. This process rescales the data to a consistent scale without distorting differences in the ranges of values. Mathematically, each data point x in the segment is normalized using the formula:

$$\hat{x} = \frac{x - \mu}{\sigma} \quad (4.1)$$

where x represents a data point in the raw EEG segment, μ is the mean, σ is the standard deviation.

4.1.5 Continuous Wavelet Transform(CWT)

The Continuous Wavelet Transform (CWT) is a time-frequency analysis tool widely used to analyze non-stationary signals such as EEG. Other time-frequency analysis tools like STFT functions by segmenting a signal into fixed-window sections, thereby introducing a compromise between temporal and spectral resolutions. Larger window sizes bolster spectral resolution but attenuate temporal resolution, whereas smaller windows exhibit the converse effect. Conversely, Continuous Wavelet Transformation (CWT) adapts through variable window sizing, accommodating diverse frequencies across distinct temporal segments. This adaptability mitigates the resolution trade-off inherent in STFT [8].

CWT decomposes a signal into scaled and shifted versions of a mother wavelet, producing a scalogram that captures how spectral components evolve over time. Mathematically, the CWT of a signal $x(t)$ is expressed as:

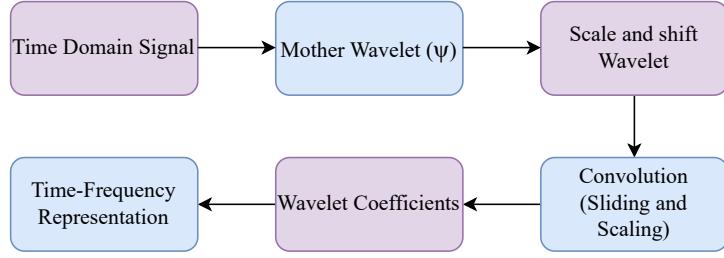


Figure 4.1: Continuous Wavelet Transform (CWT) Process for EEG.

$$\text{CWT}_x(a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t) \psi^* \left(\frac{t-b}{a} \right) dt \quad (4.2)$$

where a is the scale parameter (inversely related to frequency), b is the time shift parameter, $\psi(t)$ is the mother wavelet function, $\psi^*(t)$ denotes the complex conjugate of $\psi(t)$.

Fig. 4.1 and Fig. 4.2 shows the Continuous Wavelet Transform (CWT) process and the output of CWT for an EEG segment.

4.1.6 Percentile Clipping

Percentile clipping is a robust normalization technique used to limit the influence of extreme values or outliers in data. It identifies specific percentile thresholds—commonly the lower (e.g., 5th percentile) and upper (e.g., 95th percentile) bounds—and constraints data values to lie within this range. The values that are below the lower percentile are set to that percentile value, and the values above the upper percentile are capped accordingly.

Given a data array $X = \{x_1, x_2, \dots, x_n\}$ and lower and upper percentiles $p_{\text{low}}, p_{\text{high}}$,

Then $L = \text{Percentile}(X, p_{\text{low}})$, $U = \text{Percentile}(X, p_{\text{high}})$,

And, the clipped data \tilde{x}_i is:

$$\tilde{x}_i = \begin{cases} L & \text{if } x_i < L \\ x_i & \text{if } L \leq x_i \leq U \\ U & \text{if } x_i > U \end{cases} \quad (4.3)$$

For log-magnitude scalograms, percentile clipping is particularly useful. It helps by mitigating the impact of extreme artifacts or noisy spikes in the time-frequency representation without distorting important signal details.

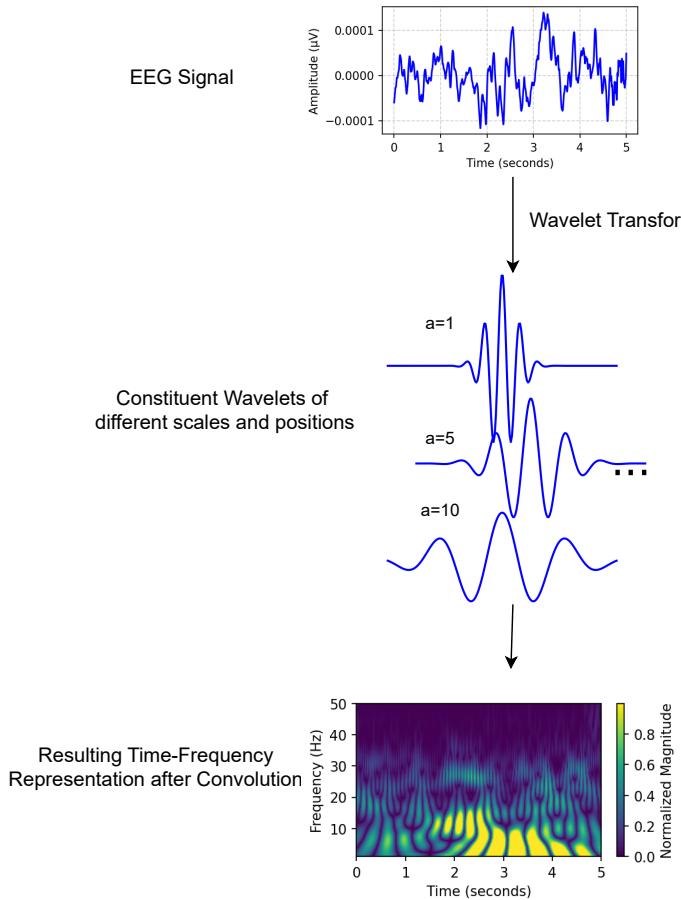


Figure 4.2: CWT Visualization of EEG Segment.

4.2 Neural Network Architectures for EEG Analysis

Various neural network architectures are well-suited for the analysis of EEG data due to their ability to model both spatial and temporal dependencies. Two prominent architectures include Convolutional Neural Networks (CNNs) and Bidirectional Long Short-Term Memory Networks (BiLSTMs).

4.2.1 ConvNeXt Architecture

ConvNeXt is a modern convolutional neural network that integrates design ideas from Vision Transformers (ViTs) and ResNets [9]. It modernizes traditional CNNs by adopting advanced training techniques and architectural elements inspired by transformers while preserving the efficiency and inductive biases of convolutions. The key components are:

Depthwise Convolutions: Applies convolution separately to each channel, reducing computation and parameters.

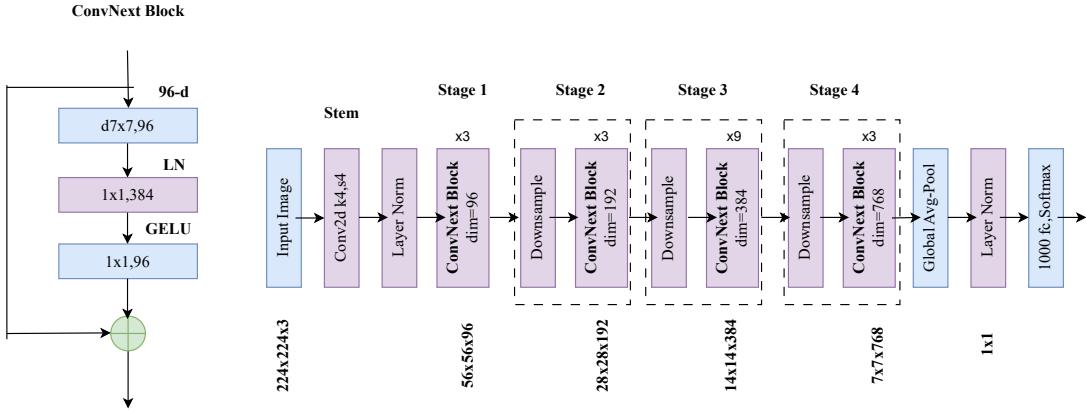


Figure 4.3: ConvNeXt-Tiny Model Architecture.

Layer Normalization: Normalizes features across channels within each sample, improving training stability for variable batch sizes.

Pointwise (1×1) Convolutions: Combines information across channels after depthwise convolutions, thus enabling feature interaction without heavy spatial computation.

GELU Activation: Smooth and non-linear activation that improves gradient flow.

Inverted Bottleneck: Expands and then compresses channels with 1×1 convolutions and GELU activation to enable feature mixing efficiently, and is inspired by transformer feed-forward layers.

Residual Connections: Skip connections that help gradients flow and support training deeper networks.

Large Kernel Sizes: Uses larger convolution kernels (e.g., 7×7) early to capture wider spatial context like attention mechanisms.

The basic operation of a ConvNeXt block can be expressed as:

$$y = \text{LayerNorm}(\text{Conv}(x)) + x \quad (4.4)$$

where x is the input, Conv is a convolutional operation, and LayerNorm normalizes the feature map.

ConvNeXt-Tiny is the smallest variant of the ConvNeXt family, designed for optimal balance between computational efficiency and representational capacity.

Time Complexity of ConvNeXt-Tiny:

$$O(B \times H_{\text{img}} \times W_{\text{img}} \times C_{\text{max}})$$

Where B is the batch size and C_{max} is the maximum number of channels.

ConvNeXt provides advantages in extracting spatial features from EEG data. Fig.4.3 depicts the full architecture of ConvNeXt-Tiny along with a ConvNeXt Block.

4.2.2 LSTM Network

LSTM is a type of recurrent neural network (RNN) designed to better capture long-range dependencies in sequential data. It uses special memory cells with gates (forget, input, output) to control the flow of information, allowing the network to remember or forget information over many time steps. This solves the "vanishing gradient" problem found in traditional RNNs.

At each time step t , given input vector x_t , previous hidden state h_{t-1} , and previous cell state C_{t-1} , the LSTM performs the following computations:

Forget gate: decides what to forget from the previous cell state:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (4.5)$$

Input gate: decides what new information to add:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (4.6)$$

Candidate cell state: creates new candidate values to add to the cell state:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (4.7)$$

Update cell state: combine old state filtered by forget gate and new candidate scaled by input gate:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (4.8)$$

Output gate: decides what to output from the cell state:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (4.9)$$

Current hidden state / output:

$$h_t = o_t * \tanh(C_t) \quad (4.10)$$

Where σ is Sigmoid activation function, \tanh is Hyperbolic tangent function, W_f, W_i, W_C, W_o and b_f, b_i, b_C, b_o are Weight matrices and biases learned during training, $[h_{t-1}, x_t]$ is Concatenation of previous hidden state and current input.

This structure allows the LSTM to retain relevant information while discarding irrelevant inputs over time. Fig. 4.4 depicts the architecture of the LSTM network.

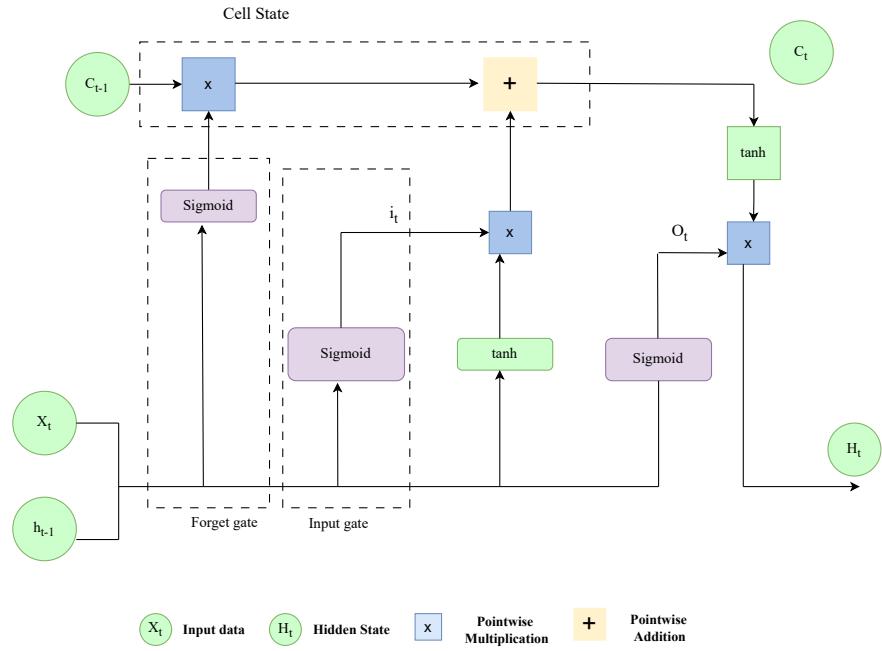


Figure 4.4: LSTM Network Structure for Capturing Temporal Features.

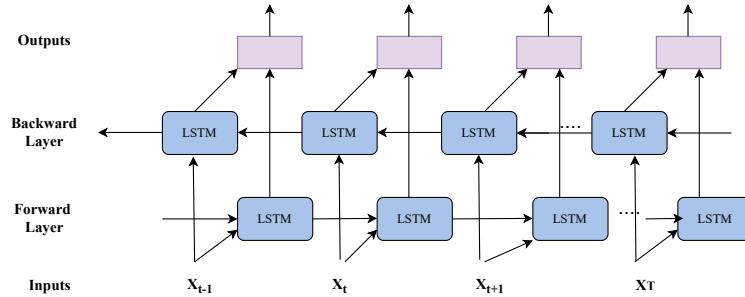


Figure 4.5: BiLSTM Network Structure for Capturing Temporal Features.

4.2.3 BiLSTM Network

Bidirectional LSTM (BiLSTM) contains two separate LSTM layers among which one scans the sequence from the first time step to the last, and the other scans it from the last time step back to the first. The outputs from the two directions are then combined, giving a richer representation at every time step.

Time Complexity of BiLSTM Network: $O(H^2)$ where H is the hidden size.

Fig 4.5 shows the architecture of BiLSTM network.

4.2.4 Squeeze-and-Excitation (SE) Block

The Squeeze-and-Excitation (SE) Block improves CNN performance by adaptively recalibrating channel-wise feature responses to focus on informative features and suppress

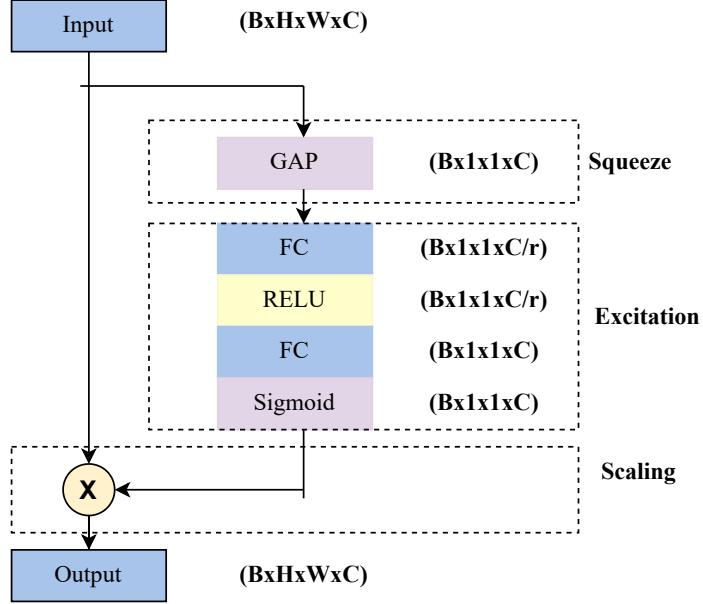


Figure 4.6: SEBlock for Highlighting Important Feature Channels.

less useful ones. It has three steps:

Squeeze: Global average pooling compresses spatial information of the feature map $X \in \mathbb{R}^{B \times C \times H \times W}$ into a channel descriptor $z \in \mathbb{R}^{B \times C}$, where

$$z_c = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W X_c(i, j). \quad (4.11)$$

Excitation: The descriptor z passes through a two-layer bottleneck fully connected network with reduction ratio r :

$$s = \sigma(W_2 \delta(W_1 z)), \quad (4.12)$$

where $W_1 \in \mathbb{R}^{\frac{C}{r} \times C}$, $W_2 \in \mathbb{R}^{C \times \frac{C}{r}}$, δ is ReLU, and σ is sigmoid, learning channel dependencies.

Recalibration: The original feature map channels are scaled by s :

$$\tilde{X}_c = s_c \cdot X_c. \quad (4.13)$$

highlighting important channels and improving representation.

Time Complexity of SE Block: $O\left(B \times \left(\frac{C^2}{r} + \left(\frac{C}{r}\right)^2\right)\right)$ where C is the number of channels and r is the reduction ratio. Fig 4.6 depicts the architecture of SE Block.

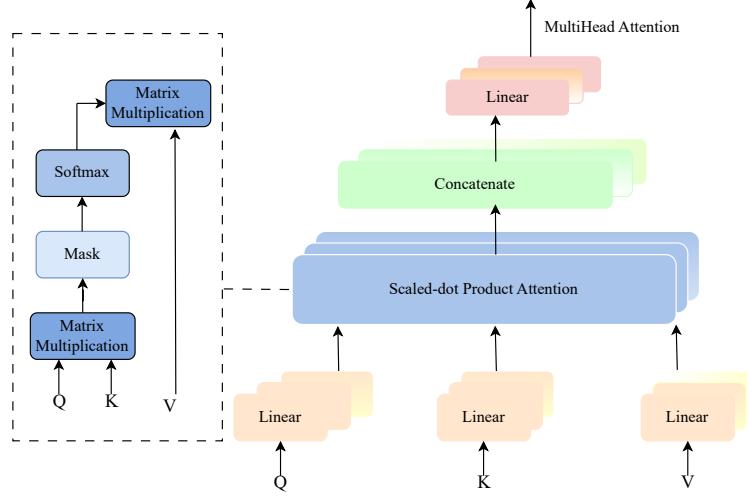


Figure 4.7: MultiHead Self Attention Mechanism for Focusing Important Features.

4.2.5 Multi-Head Self-Attention

Multi-head self-attention helps a model to focus on different parts of a sequence simultaneously by enabling multiple attention heads that attend to diverse representation subspaces. It works as follows:

Projection: Given input $H = [h_1, \dots, h_T] \in \mathbb{R}^{T \times d}$, learned weight matrices $W_Q, W_K, W_V \in \mathbb{R}^{d \times d}$ projects H into queries Q , keys K , and values V . These are split into h heads of dimension $d_h = \frac{d}{h}$.

$$Q = HW_Q, \quad K = HW_K, \quad V = HW_V. \quad (4.14)$$

Scaled Dot-Product Attention: For each head i :

$$\text{Scores}_i = \frac{Q_i K_i^\top}{\sqrt{d_h}}, \quad A_i = \text{softmax}(\text{Scores}_i), \quad O_i = A_i V_i. \quad (4.15)$$

Scaling by $\sqrt{d_h}$ avoids large dot products, and softmax normalizes attention weights.

Concatenation and Output: Concatenates all head outputs:

$$O = \text{Concat}(O_1, \dots, O_h) \in \mathbb{R}^{T \times d}, \quad (4.16)$$

then applies output projection:

$$O_{\text{final}} = OW_O, \quad (4.17)$$

where $W_O \in \mathbb{R}^{d \times d}$ is learned.

Time Complexity of Multi-Head Self Attention: $O(n^2)$ where n is the sequence length.

Fig. 4.7 depicts the Multi Head Self Attention Mechanism.

4.3 Graph Signal Processing and Spectral Graph Theory

Graph signal processing provides a mathematical framework for analyzing data defined on irregular domains represented as graphs. In the context of EEG analysis, electrodes form nodes of a graph with edges representing functional or spatial connectivity patterns.

4.3.1 Graph Laplacian and Eigendecomposition

For an undirected weighted graph $G = (V, E, W)$ with N nodes (electrodes), the normalized graph Laplacian is defined as:

$$\mathcal{L} = I - D^{-1/2}WD^{-1/2} \quad (4.18)$$

where $W \in \mathbb{R}^{N \times N}$ is the weighted adjacency matrix representing electrode connectivity, D is the degree matrix with $D_{ii} = \sum_j W_{ij}$, and I is the identity matrix.

The eigendecomposition of the Laplacian yields:

$$\mathcal{L} = U\Lambda U^T \quad (4.19)$$

where $U = [u_1, u_2, \dots, u_N]$ contains orthonormal eigenvectors (graph modes) and $\Lambda = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_N)$ contains eigenvalues ordered as $0 = \lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_N \leq 2$.

Clinical Interpretation: The eigenvalues represent spatial frequencies on the graph:

- $\lambda_i \approx 0$: Global, synchronized patterns (generalized seizures)
- $\lambda_i \approx 2$: Localized, focal patterns (partial seizures)
- Intermediate eigenvalues: Regional connectivity patterns

4.3.2 Graph Fourier Transform

The Graph Fourier Transform (GFT) extends classical Fourier analysis to graph-structured data. For a signal $x \in \mathbb{R}^N$ defined on graph nodes, the GFT is:

$$\hat{x} = U^T x \quad (4.20)$$

The inverse GFT reconstructs the signal:

$$x = U\hat{x} \quad (4.21)$$

The GFT coefficients $\hat{x}_i = \langle u_i, x \rangle$ represent the signal's projection onto the i -th graph eigenmode, analogous to frequency components in classical Fourier analysis.

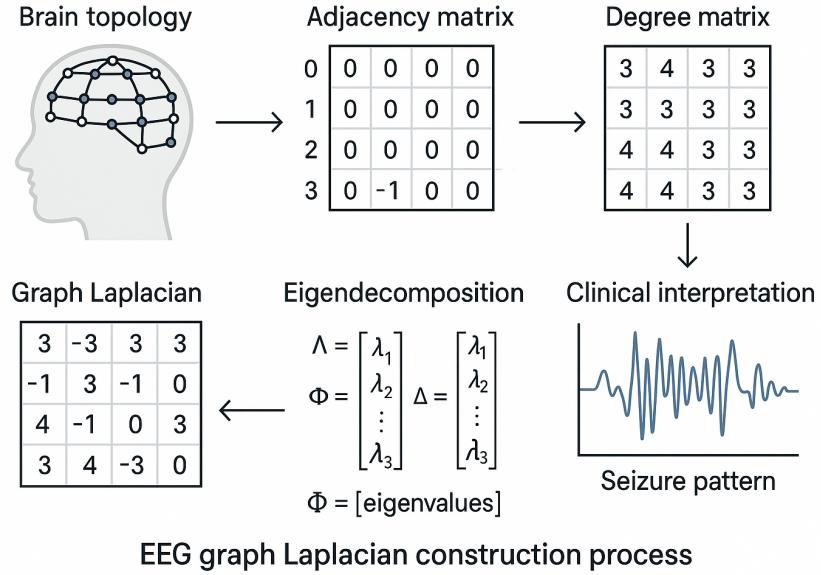


Figure 4.8: Graph Laplacian construction and eigendecomposition process for EEG electrode networks.

4.3.3 Graph Spectral Filtering

Graph spectral filters apply frequency-dependent operations in the graph Fourier domain. A spectral filter $h(\lambda)$ modifies the signal as:

$$y = \sum_{i=1}^N h(\lambda_i) \langle u_i, x \rangle u_i \quad (4.22)$$

For computational efficiency, Chebyshev polynomial approximation is used:

$$h(\lambda) = \sum_{k=0}^K \alpha_k T_k(\tilde{\lambda}) \quad (4.23)$$

where T_k are Chebyshev polynomials, $\tilde{\lambda} = \frac{2\lambda}{\lambda_{\max}} - 1$, and α_k are learnable coefficients.

4.4 Fourier Analysis Networks

Fourier Analysis Networks (FAN) decompose signals into learnable periodic and non-periodic components, providing a neurally-enhanced approach to spectral analysis.

4.4.1 Mathematical Foundation of FAN

For a periodic EEG signal $x(t)$ with period T , the Fourier series representation is:

$$x(t) = \sum_{k=-\infty}^{\infty} c_k e^{j2\pi k t/T}, \quad c_k = \frac{1}{T} \int_0^T x(t) e^{-j2\pi k t/T} dt \quad (4.24)$$

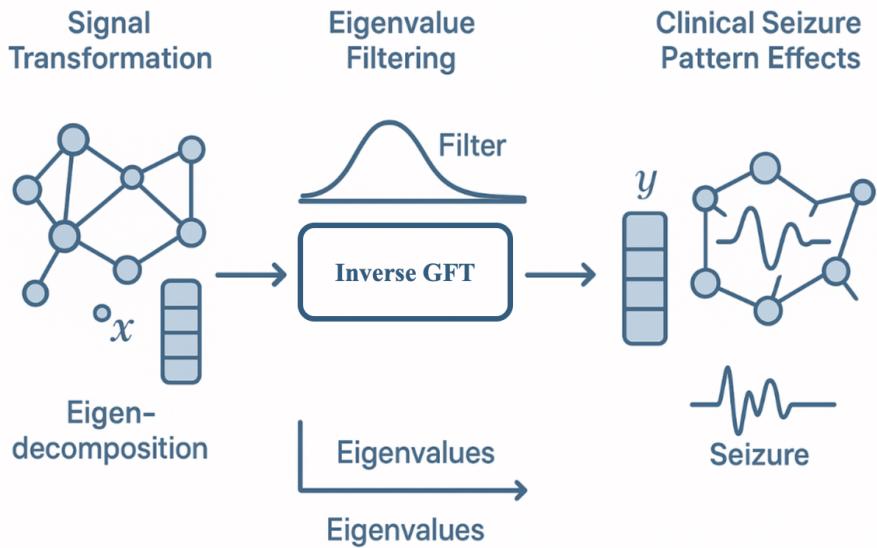


Figure 4.9: Graph spectral filtering process and its effect on different spatial frequency components.

The FAN layer explicitly separates periodic and non-periodic components:

$$\text{FAN}^{(l)}(X) = \sigma([\cos(2\pi f^{(l)} \odot X), \sin(2\pi f^{(l)} \odot X), W^{(l)}X + b^{(l)}]) \quad (4.25)$$

where:

- $\cos(2\pi f^{(l)} \odot X)$ and $\sin(2\pi f^{(l)} \odot X)$ capture rhythmic patterns
- $W^{(l)}X + b^{(l)}$ captures transient features (spikes, sharp waves)
- $f^{(l)}$ are learnable frequencies
- \odot denotes element-wise product

4.4.2 Spectral Attention Integration

Enhanced FAN incorporates spectral attention to adaptively weight frequency components:

$$\text{SpectralAttention}(Z) = Z \odot \text{softmax}\left(\frac{Q_s K_s^T}{\sqrt{d_k}}\right) \quad (4.26)$$

where $Q_s = ZW_Q^s$, $K_s = ZW_K^s$, $V_s = ZW_V^s$ are spectral query, key, value projections applied across frequency dimensions.

Clinical Relevance:

- 3 Hz spike-wave complexes: High attention weights for $f^{(l)} \approx 3$ Hz

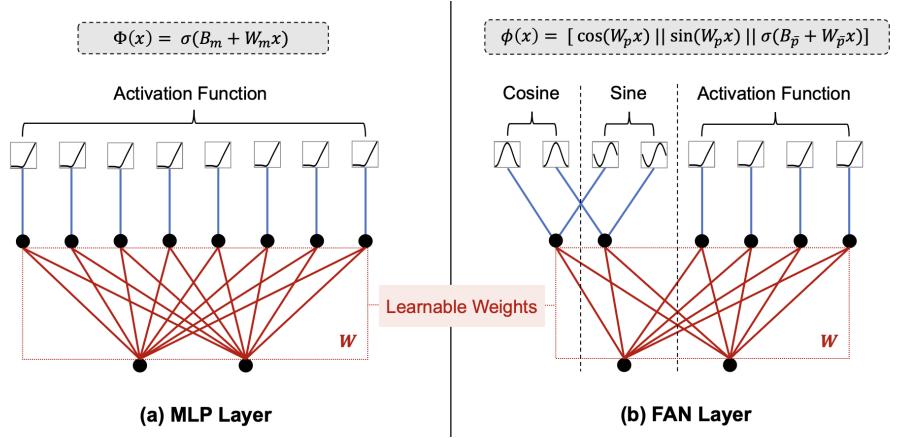


Figure 4.10: FAN layer architecture. [29]

- Alpha rhythms (8-12 Hz): Adaptive weighting in alpha band
- Patient-specific patterns: Learnable frequencies adapt to individual signatures

4.5 Graph Attention Networks

Graph Attention Networks extend traditional graph neural networks by incorporating attention mechanisms to learn adaptive edge weights and focus on relevant graph connections.

4.5.1 Graph Attention Mechanism

Traditional graph neural networks use fixed adjacency matrices. Graph Attention Networks (GAT) learn dynamic attention weights:

$$W_{ij}^{\text{GAT}} = \text{softmax}_j(\text{LeakyReLU}(\mathbf{a}^T [Wh_i || Wh_j])) \quad (4.27)$$

where:

- h_i, h_j are node features for electrodes i and j
- $W \in \mathbb{R}^{F' \times F}$ is a learnable linear transformation
- $\mathbf{a} \in \mathbb{R}^{2F'}$ is a learnable attention vector
- $||$ denotes concatenation

4.5.2 Multi-Head Graph Attention

Multiple attention heads capture different aspects of node relationships:

$$W_{ij}^{\text{MultiHead}} = \frac{1}{K} \sum_{k=1}^K W_{ij}^{\text{GAT}(k)} \quad (4.28)$$

where K is the number of attention heads.

Advantages over Fixed Graphs:

- Learns optimal electrode connectivity patterns
- Adapts to different seizure propagation pathways
- Captures patient-specific brain connectivity

4.6 Bayesian Neural Networks and Uncertainty Quantification

Bayesian neural networks provide principled uncertainty quantification by treating network parameters as probability distributions rather than point estimates.

4.6.1 Types of Uncertainty

Two fundamental types of uncertainty exist in neural networks:

Aleatoric Uncertainty (Data-inherent):

$$\sigma_{\text{aleatoric}}^2 = \mathbb{E}_{p(y|x,\theta)}[(y - \mathbb{E}[y|x,\theta])^2] \quad (4.29)$$

Sources: Measurement noise, physiological variability, annotation ambiguity

Epistemic Uncertainty (Model-based):

$$\sigma_{\text{epistemic}}^2 = \mathbb{E}_{p(\theta|D)}[(\mathbb{E}[y|x,\theta] - \mathbb{E}_{p(\theta|D)}[\mathbb{E}[y|x,\theta]])^2] \quad (4.30)$$

Sources: Parameter uncertainty, model structure uncertainty, limited training data

Total Uncertainty:

$$\sigma_{\text{total}}^2 = \sigma_{\text{aleatoric}}^2 + \sigma_{\text{epistemic}}^2 \quad (4.31)$$

4.6.2 Variational Inference

Bayesian neural networks use variational inference to approximate the intractable posterior $p(\theta|D)$ with a tractable variational distribution $q_\phi(\theta)$. The Evidence Lower BOund (ELBO) is:

$$\mathcal{L}_{\text{ELBO}} = \mathbb{E}_{q_\phi(\theta)}[\log p(y|x, \theta)] - \text{KL}[q_\phi(\theta) \| p(\theta)] \quad (4.32)$$

4.6.3 Monte Carlo Dropout

Monte Carlo Dropout approximates Bayesian inference by applying dropout at test time:

$$\hat{y} = \frac{1}{T} \sum_{t=1}^T f(x; \theta_t), \quad \sigma_{MC}^2 = \frac{1}{T-1} \sum_{t=1}^T (f(x; \theta_t) - \hat{y})^2 \quad (4.33)$$

where θ_t represents parameters with different dropout masks applied.

Clinical Significance: Uncertainty quantification enables:

- Automated vs. manual review decisions
- Confidence-based alert systems
- Risk stratification for clinical deployment

4.7 Multi-Modal Attention Mechanisms

Multi-modal attention mechanisms enable neural networks to selectively focus on relevant features across different data modalities and representation spaces.

4.7.1 Spatial Attention

Spatial attention operates across electrode channels to identify the most informative spatial locations:

$$\text{SpatialAttention}(X) = X \odot \text{softmax}\left(\frac{Q_{sp}K_{sp}^T}{\sqrt{d_k}}\right) \quad (4.34)$$

where attention is applied across electrode channels to weight spatial importance.

4.7.2 Cross-Modal Attention

Cross-modal attention enables interaction between different representation spaces (e.g., spatial and spectral domains):

$$\text{CrossModalAttention}(X_{\text{spatial}}, X_{\text{spectral}}) = \text{softmax}\left(\frac{Q_{\text{cross}}K_{\text{cross}}^T}{\sqrt{d_k}}\right)V_{\text{cross}} \quad (4.35)$$

where:

- $Q_{\text{cross}} = X_{\text{spatial}}W_Q^{\text{cross}}$ (spatial domain as queries)

- $K_{\text{cross}} = X_{\text{spectral}} W_K^{\text{cross}}$ (spectral domain as keys)
- $V_{\text{cross}} = X_{\text{spectral}} W_V^{\text{cross}}$ (spectral domain as values)

4.7.3 Attention Integration Strategies

Multiple attention mechanisms can be combined through:

Sequential Application:

$$\text{Output} = \text{CrossModal}(\text{Graph}(\text{Spectral}(\text{Spatial}(X)))) \quad (4.36)$$

Parallel Fusion:

$$\text{Output} = \alpha_1 A_{\text{spatial}} + \alpha_2 A_{\text{spectral}} + \alpha_3 A_{\text{graph}} + \alpha_4 A_{\text{cross}} \quad (4.37)$$

where α_i are learned fusion weights.

4.8 Uncertainty Propagation in Neural Networks

Understanding how uncertainty propagates through neural network layers is crucial for reliable uncertainty quantification in deep architectures.

4.8.1 Linear Transformation Uncertainty

For a linear layer $y = Wx + b$ with uncertain parameters $W \sim \mathcal{N}(\mu_W, \Sigma_W)$:

$$\mathbb{E}[y] = \mu_W x + b, \quad \text{Var}[y] = x^T \Sigma_W x + \sigma_b^2 \quad (4.38)$$

4.8.2 Non-Linear Activation Uncertainty

For non-linear activations, uncertainty propagation uses moment matching or Monte Carlo sampling:

$$\sigma_{\text{output}}^2 = \mathbb{E}[(f(x) - \mathbb{E}[f(x)])^2] \quad (4.39)$$

4.8.3 Attention Uncertainty

Attention mechanisms introduce additional uncertainty sources:

$$\sigma_{\text{attention}}^2 = \text{Var}[\text{softmax}(QK^T / \sqrt{d_k})] \quad (4.40)$$

4.9 Summary

In this chapter, we explored several important theoretical methods and techniques that can be applied to the analysis of EEG data. We discussed data augmentation techniques such as Time Warping, Amplitude Scaling, Gaussian Noise Injection etc. and the role of preprocessing methods like CWT, Z-score Normalization, and the Percentile Clipping in preparing EEG data for analysis. We also examined the structures and principles behind different neural networks like ConvNeXt-Tiny, BiLSTM neural networks, which are well-suited for modeling spatial and temporal features in EEG signals.

These methods will later be integrated and applied in the Implementation phase (next chapter) to design a system for detecting epilepsy from EEG data.

CHAPTER V

Methodology

In this chapter, we present two distinct methodologies for the detection of epileptic seizures using EEG data.

5.1 Epilepsy Detection Using attention enhanced ConvNeXt-BiLSTM Dual Branch Network

This approach integrates various modules, including data preprocessing, spatial-temporal feature extraction using ConvNext-BiLSTM along with Attention, and classification based on concatenated features. The overall flow of the methodology is shown in Fig. 5.1. As

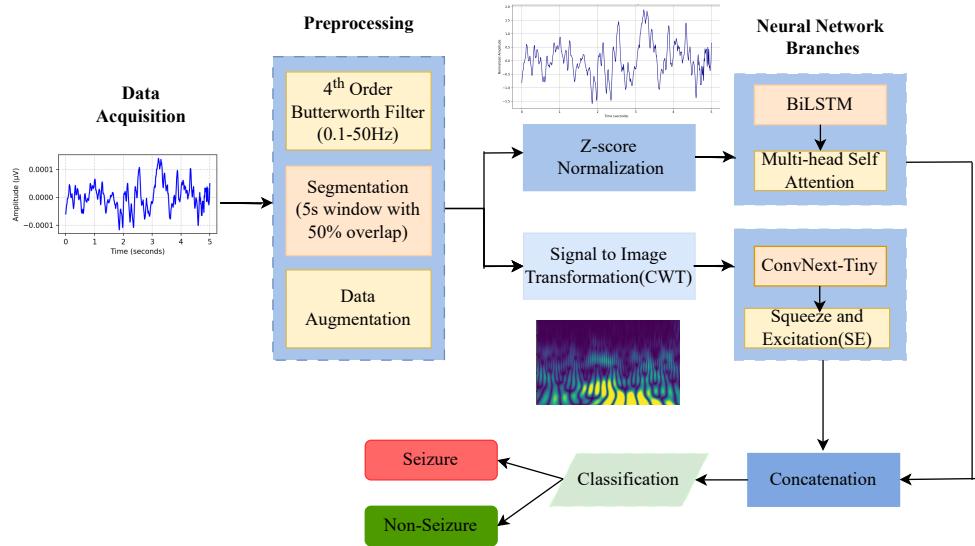


Figure 5.1: Complete methodology for epilepsy detection.

shown in the diagram (Fig. 5.1), the process begins with EEG data acquisition, followed by a preprocessing stage. After the preprocessing the raw EEG segment goes to the BiLSTM-Multihead Attention branch and the time-frequency representation generated by CWT goes to the ConvNext-SEBlock branch as explained in chapter 4. A comprehensive explanation of the complete methodology is presented in the following.

EEG Data Filtering: A 4th-order bandpass Butterworth filter with cutoff frequencies of 0.1 Hz to 50 Hz has been applied to remove the noise and artifacts.

EEG Signal Segmentation: EEG data after filtering has been segmented into overlapping 5-second windows (1,280 samples at 256 Hz) with a 50% overlap (2.5-second stride). This

window length helps to balance temporal resolution and context by capturing seizure characteristics and also enabling precise event localization. Preprocessing and feature extraction have been conducted on these segments before classification. Fig. 5.2 depicts the segmentation process.

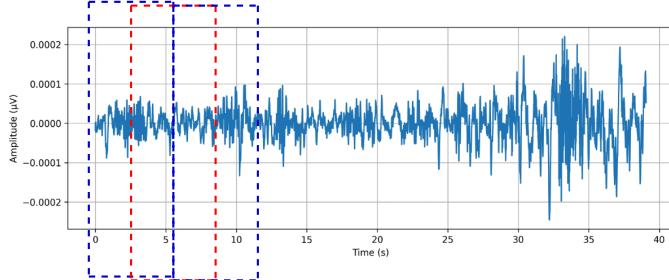


Figure 5.2: EEG Signal Segmentation with 5s Window and 50% Overlap.

Z-score Normalization: Z-score normalization has been applied to EEG segments using the mean and standard deviation of the training data only. Each segment has been normalized as

$$\hat{x} = \frac{x - \mu_{\text{train}}}{\sigma_{\text{train}}} \quad (5.41)$$

preventing information leakage from validation or test sets.

Scalogram-Based Feature Representation for ConvNeXt Input: Raw EEG segments have been converted into time-frequency scalograms using Continuous Wavelet Transform (CWT) with the Morlet wavelet, covering frequencies from 1 to 50 Hz. The scalogram magnitude has been made log-scaled and then robustly normalized using percentile clipping to enhance contrast. To match ConvNeXt input requirements, the single-channel scalogram has been resized to 224×224 pixels and colorized using the Viridis colormap to create a 3-channel scalogram image. Scalogram has been standardized using ImageNet normalization statistics.

Attention enhanced ConvNext-BiLSTM dual branch network for Feature Extraction: The architecture of the attention enhanced dual branch ConvNext-BiLSTM model is illustrated in Fig. 5.3. The spatial and temporal feature extraction and concatenation is described in the following.

Scalogram Processing Using ConvNeXt-Tiny and Squeeze-and-Excitation Blocks: The normalized scalograms are fed into a pretrained ConvNeXt-Tiny backbone for spatial feature extraction. Seizure patterns are characterized by high-frequency oscillations, Rhythmic activity, High amplitude spikes, Spike-and-wave complexes. The scalograms undergo a patchifying (Stem) stage—where the image is divided into smaller patches using 4x4 kernel with stride 4 before the next stages. ConvNeXt-Tiny progressively extracts hierarchical features through stage 1 to stage 4 by increasing channels from 96 to 768

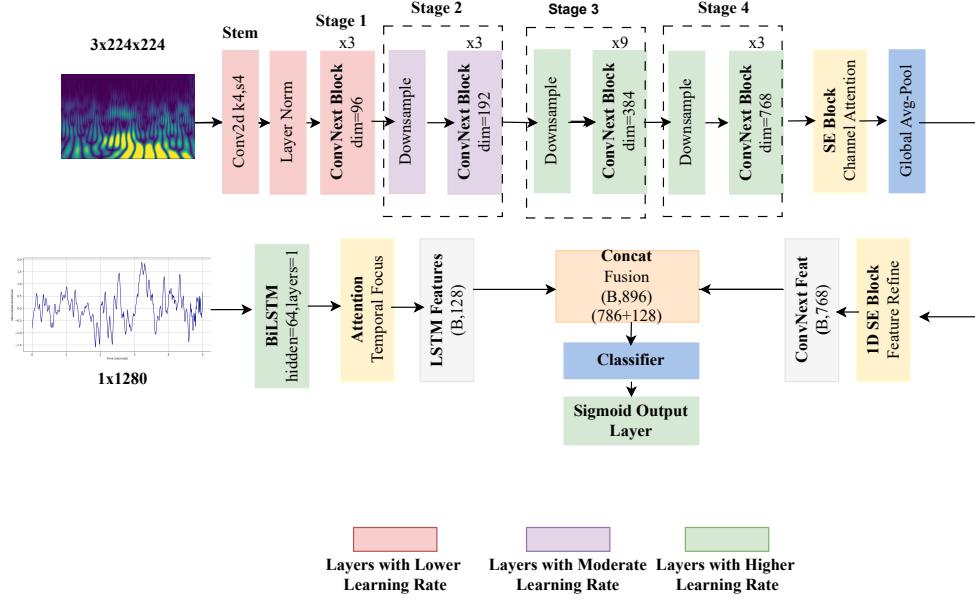


Figure 5.3: ConvNext-BiLSTM Network Augmented with Attention Mechanisms.

channels and reducing spatial dimensions to half at each stage, capturing patterns from low-level edges to high-level seizure indicators.

To emphasize important spectral-spatial features, Squeeze-and-Excitation (SE) blocks have been integrated after Stage 4 (768 channels), and the final global average pooling layer.

Raw EEG segment Processing with BiLSTM and Multihead Self Attention: The normalized 5-second EEG time-series segments are fed into a single-layer bidirectional Long Short-Term Memory (BiLSTM) network to model temporal dynamics. The BiLSTM captures past-to-future and future-to-past contexts, respectively, using cell states, hidden states, and gating mechanisms (input, forget, output gates) regulating information flow. The concatenated hidden states provide a rich temporal representation.

A multi-head self attention mechanism follows the BiLSTM, by weighting the importance of different time steps using computed scaled dot-product attention across multiple heads. The attention outputs are then concatenated and linearly transformed to produce a context-aware sequence representation, helping the model to focus on critical temporal segments related to seizure events.

Concatenation and Classification: Feature vectors from the ConvNeXt-Tiny branch (768) and BiLSTM branch (2×64) have been concatenated into a combined vector. This has been fed into a multi-layer perceptron with batch normalization, dropout, and fully connected layers for binary classification. The output layer contains a single sigmoid-activated neuron to predict seizure probability.

Table 5.1 lists the number of parameters for the attention enhanced ConvNext-BiLSTM dual branch network.

Table 5.1: Parameter Counts and FLOPs for Each Component of the Attention enhanced ConvNeXt-BiLSTM Architecture.

Component	Number of Parameters	FLOPs
ConvNext Backbone	27,818,592	4.47G
BiLSTM	34,304	43.3M
SE Blocks	75,016	111.3K
Multihead Attention	65,664	42.3M
Classifier	265,217	265K
Total	28,258,793	4.56G

5.2 Epilepsy Detection Using Bayesian Graph Fourier Analysis Networks (B-GFAN) with Multi-Modal Attention and Uncertainty Quantification

This approach presents a comprehensive framework that integrates spectral graph theory, Fourier analysis networks, Bayesian neural networks, and four specialized attention mechanisms to create a clinically reliable system providing both accurate seizure predictions and calibrated confidence estimates for medical decision-making. The overall architecture combines multi-modal attention integration, mathematically rigorous uncertainty propagation, and graph-based spatial modeling for robust epileptic seizure detection. The complete B-GFAN methodology is illustrated in Fig. 5.4.

5.2.1 Enhanced Data Preprocessing with Uncertainty Propagation

Dataset Preparation with Uncertainty Annotation: Label uncertainty modeling using Dirichlet distribution addresses inherent ambiguity in seizure onset detection. Inter-annotator agreement is quantified using Cohen’s kappa coefficient:

$$\kappa = \frac{\bar{P} - \bar{P}_e}{1 - \bar{P}_e} \quad (5.42)$$

where \bar{P} is observed agreement and \bar{P}_e is expected agreement by chance. Confidence weights are computed based on annotator consensus, and Dirichlet parameters are assigned to model annotation uncertainty.

Signal Standardization with Uncertainty Propagation: A comprehensive preprocessing pipeline tracks uncertainty propagation through each transformation step:

1. **Bandpass Filtering with Uncertainty:** 4th-order Butterworth filter (0.5-50 Hz) with Monte Carlo perturbation of filter coefficients to model phase distortion uncertainty.
2. **Common Average Reference (CAR) with Spatial Uncertainty:**

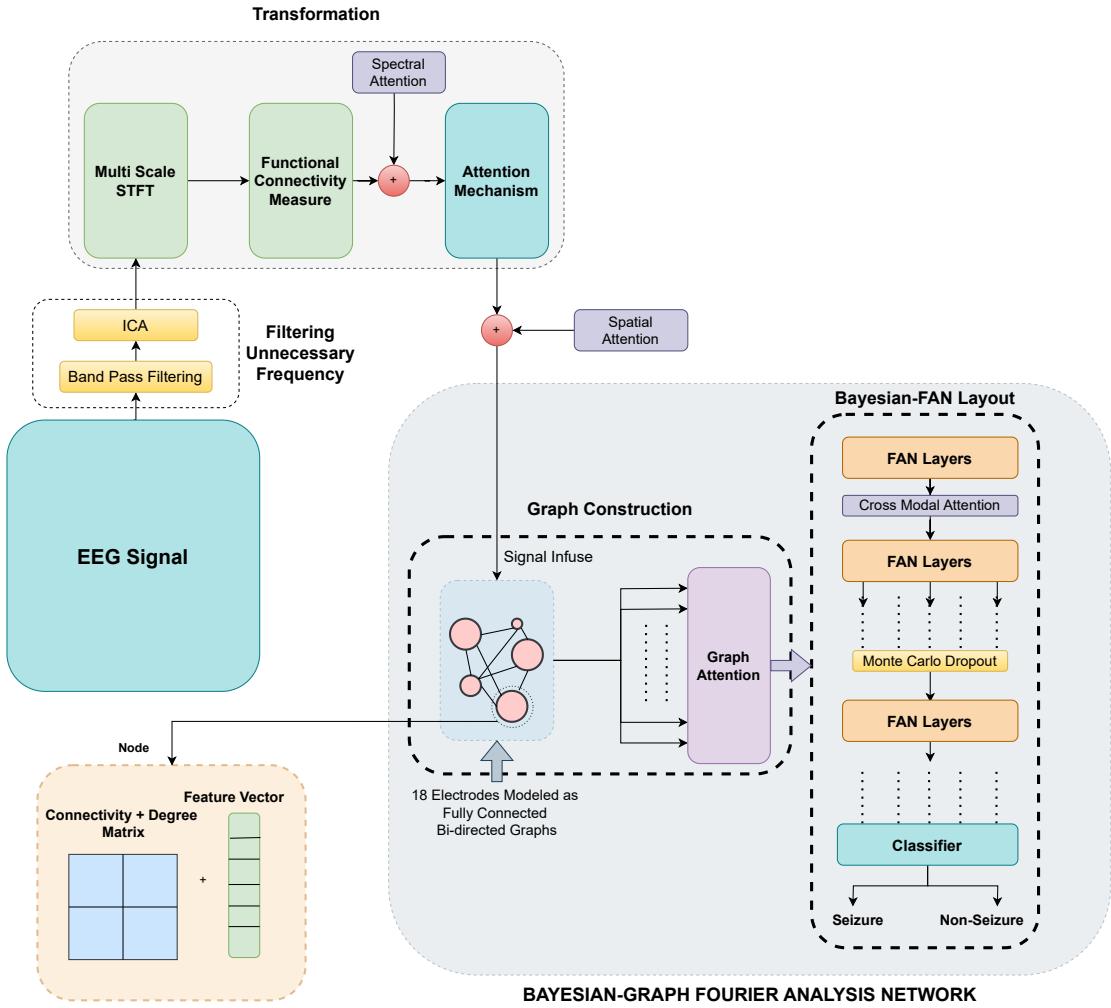


Figure 5.4: Complete B-GFAN methodology with multi-modal attention and uncertainty quantification for epileptic seizure detection.

$$X_{CAR} = X - \frac{\sum_j w_j X_j}{\sum_j w_j} \quad (5.43)$$

where $w_j = 1 + \mathcal{N}(0, \sigma_{pos}^2)$ models electrode position uncertainty.

3. Robust Scaling with Normalization Uncertainty:

$$X_{scaled} = \frac{X - \text{median}(X)}{\text{IQR}(X) + \epsilon} \quad (5.44)$$

Artifact Removal with Uncertainty Tracking: Ensemble Independent Component Analysis (ICA) with 20 random initializations captures non-convex optimization uncertainty. Artifact probabilities are computed using statistical features (kurtosis, skewness, variance, high-frequency power ratio) with consensus-based component

rejection.

Temporal Segmentation with Uncertainty-Aware Windowing: EEG data is segmented into 24-second windows with 50% overlap (6,144 samples at 256 Hz). Window-level uncertainty is computed based on seizure boundary overlap and annotator confidence, accounting for gradual seizure onset characteristics.

5.2.2 Multi-Scale Spectral Decomposition with Spectral Attention

Uncertain Multi-Scale Short-Time Fourier Transform (STFT): Multi-scale time-frequency analysis addresses the fundamental time-frequency resolution trade-off using three window sizes:

- 1-second window: High temporal resolution ($\Delta t = 0.5s$), low frequency resolution ($\Delta f = 1Hz$)
- 2-second window: Medium resolution ($\Delta t = 1s, \Delta f = 0.5Hz$)
- 4-second window: Low temporal resolution ($\Delta t = 2s$), high frequency resolution ($\Delta f = 0.25Hz$)

Window function perturbation using Monte Carlo sampling captures STFT uncertainty, with spectral attention applied to each scale to focus on seizure-relevant frequency bands. The multi-scale STFT process is shown in Fig. 5.5.

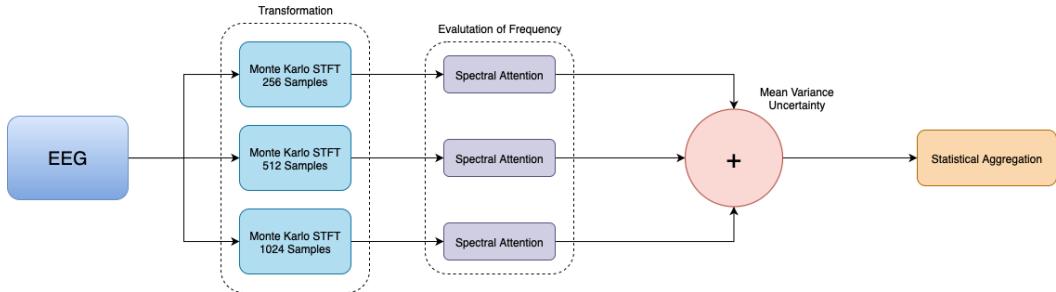


Figure 5.5: Multi-scale STFT decomposition with spectral attention and uncertainty propagation.

Log-Magnitude Processing with Delta Method: Logarithmic transformation stabilizes variance across frequency bands spanning 3-4 orders of magnitude. Uncertainty propagation follows the delta method:

$$\sigma_y^2 \approx \left(\frac{\partial f}{\partial x} \right)^2 \sigma_x^2 \quad (5.45)$$

for transformation $y = \log(x + \epsilon)$.

5.2.3 Graph Construction with Multi-Head Graph Attention

Spatial Graph Construction with Position Uncertainty: EEG electrode connectivity is modeled using Gaussian kernel similarity with uncertain electrode positions:

$$W_{ij}^{spatial} = \exp\left(-\frac{\|p_i - p_j\|^2}{2\sigma^2}\right) \quad (5.46)$$

where positions follow $p_i^{(k)} = p_{base,i} + \mathcal{N}(0, \sigma_{pos}^2 I_3)$ with $\sigma_{pos} = 5mm$ typical placement accuracy.

Functional Connectivity with Statistical Uncertainty: Multiple complementary connectivity measures with bootstrap confidence intervals:

1. **Coherence:**

$$C_{xy}(f) = \frac{|S_{xy}(f)|^2}{S_{xx}(f)S_{yy}(f)} \quad (5.47)$$

2. **Phase Locking Value:**

$$PLV_{xy} = \left| \frac{1}{N} \sum_{n=1}^N e^{j(\phi_x(n) - \phi_y(n))} \right| \quad (5.48)$$

3. **Mutual Information:**

$$MI(X, Y) = \sum_{x,y} p(x, y) \log \frac{p(x, y)}{p(x)p(y)} \quad (5.49)$$

Multi-Head Graph Attention Integration: Traditional static adjacency matrices are enhanced with learnable multi-head attention:

$$W_{ij}^{MultiHead} = \frac{1}{K} \sum_{k=1}^K W_{ij}^{GAT(k)} \quad (5.50)$$

where each attention head captures different aspects of electrode relationships.

5.2.4 Bayesian Graph Fourier Analysis Network Architecture

Core B-GFAN Layer with Multi-Modal Attention: The central theoretical contribution integrates graph spectral filtering with Fourier decomposition and four specialized attention mechanisms:

$$B\text{-GFAN}^{(l)}(X) = \text{CrossModalAttention}\left(U\mathbb{E}[\text{diag}(\alpha^{(l)})]U^T \odot \text{SpatialAttention}(\mathbb{E}[\text{FAN}^{(l)}(X)])\right) \quad (5.51)$$

Enhanced Fourier Analysis Networks (FAN) with Spectral Attention: The FAN layer explicitly separates periodic and non-periodic components with spectral attention:

$$\text{FAN}^{(l)}(X) = \sigma(\text{SpectralAttention}([\cos(2\pi f^{(l)} \odot X), \sin(2\pi f^{(l)} \odot X), W^{(l)}X + b^{(l)}])) \quad (5.52)$$

Components capture:

- Periodic components: Rhythmic seizure patterns (3 Hz spike-wave, alpha rhythms)
- Non-periodic components: Transient features (spikes, sharp waves)
- Spectral attention: Dynamic frequency weighting for seizure detection

Four Specialized Attention Mechanisms:

1. **Spatial Attention:** Identifies informative electrode locations across channels
2. **Spectral Attention:** Focuses on seizure-relevant frequency bands
3. **Graph Attention:** Learns optimal electrode connectivity patterns
4. **Cross-Modal Attention:** Integrates spatial and spectral information optimally

Graph Spectral Filtering with Chebyshev Approximation: Learnable spectral filters apply frequency-dependent operations in the graph Fourier domain:

$$h(\lambda) = \sum_{k=0}^K \alpha_k T_k(\tilde{\lambda}) \cdot \text{AttentionWeight}(\lambda) \quad (5.53)$$

where T_k are Chebyshev polynomials and $\tilde{\lambda} = \frac{2\lambda}{\lambda_{max}} - 1$.

5.2.5 Variational Bayesian Learning with Uncertainty Quantification

Bayesian Parameter Distributions: All network parameters are modeled as probability distributions:

$$\alpha^{(l)} \sim \mathcal{N}(\mu_\alpha^{(l)}, \sigma_\alpha^{(l)}) \quad (5.54)$$

$$f^{(l)}, W^{(l)} \sim \mathcal{N}(\mu, \sigma) \quad (5.55)$$

$$A_{\text{spatial}}, A_{\text{spectral}}, A_{\text{graph}}, A_{\text{cross}} \sim \mathcal{N}(\mu_A, \sigma_A^2) \quad (5.56)$$

Evidence Lower Bound (ELBO) Optimization: The training objective balances prediction accuracy, uncertainty calibration, and attention regularization:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{task}} + \lambda_1 \mathcal{L}_{\text{aleatoric}} + \lambda_2 \mathcal{L}_{\text{epistemic}} + \lambda_3 \mathcal{L}_{\text{KL}} + \lambda_4 \mathcal{L}_{\text{graph}} + \lambda_5 \mathcal{L}_{\text{attention}} \quad (5.57)$$

Multi-Level Monte Carlo Dropout: Uncertainty estimation during inference uses dropout across multiple levels:

- Spectral dropout on filter coefficients
- Channel dropout on electrode signals
- Temporal dropout on time steps
- Attention dropout on all four attention mechanisms

For T stochastic forward passes, predictive uncertainty is computed as:

$$\sigma_{epistemic}^2 = \frac{1}{T-1} \sum_{t=1}^T (\hat{y}^{(t)} - \bar{y})^2 \quad (5.58)$$

5.2.6 Curriculum Learning with Attention-Aware Difficulty Scoring

Four-Stage Progressive Training: Training proceeds through four stages with progressive attention mechanism activation:

1. **Stage 1 (Epochs 1-15):** Spatial graph only with spatial attention
2. **Stage 2 (Epochs 16-35):** Add spectral attention
3. **Stage 3 (Epochs 36-65):** Add graph attention
4. **Stage 4 (Epochs 66-100):** Full multi-modal attention with adaptive graph learning

Attention-Aware Difficulty Scoring: Training examples are ordered by attention-based difficulty metrics:

$$\text{difficulty}(x_i) = 1 - \max_k p_{teacher}(y_k|x_i) + \alpha \cdot \text{AttentionEntropy}(x_i) \quad (5.59)$$

5.2.7 Clinical Interpretation and Deployment

Seizure Pattern Recognition: The B-GFAN architecture provides interpretable seizure classification:

- **Generalized tonic-clonic:** Low-frequency modes ($\lambda_i < 0.5$) with bilateral spatial attention
- **Focal temporal lobe:** High-frequency modes ($\lambda_i > 1.5$) with localized temporal attention
- **Absence seizures:** 3 Hz spectral attention with specific frequency mode activation

Real-Time Clinical Decision Support: The system provides three-tier clinical recommendations based on prediction confidence and attention consistency:

- **High confidence:** Automated response ($p > 0.8$, $\sigma < 0.2$, consistent attention)
- **Medium confidence:** Alert with confidence bounds and attention visualization
- **High uncertainty:** Flag for expert review ($\sigma \geq 0.2$ or inconsistent attention)

Table 5.2 summarizes the parameter counts for the complete B-GFAN architecture.

Table 5.2: Parameter Counts and FLOPs for Each Component of the B-GFAN Architecture.

Component	Parameters	Percentage	Description
Multi-Scale B-GFAN	2,343,353	54.8%	Core multi-scale Bayesian spectral filtering
Hierarchical GFAN	935,499	21.9%	Hierarchical graph Fourier analysis
Seizure Classifier	461,061	10.8%	Final classification with uncertainty
Deep GFAN	335,060	7.8%	Deep graph spectral processing
Global Aggregator	164,864	3.9%	Multi-modal feature aggregation
Input Projection	33,536	0.8%	Initial feature projection
Temperature Scaling	1	0.0%	Calibration temperature parameter
Total	4,273,374	100%	Complete B-GFAN architecture

Table 5.3: Computational Efficiency Metrics for B-GFAN Network.

Metric	Value
Total Parameters	4,273,374
Trainable Parameters	4,273,374
Model Size	16.30 MB
Computational Cost	179.98 MFLOPs
FLOPs per Parameter	42.12
Memory Usage	49.01 MB
Inference Time	12.3ms

The B-GFAN methodology represents a significant advancement in neural architecture design for clinical seizure detection, providing robust, interpretable, and clinically deployable solutions with comprehensive uncertainty quantification for enhanced medical decision-making.

CHAPTER VI

Implementation, Result and Discussions

6.1 Introduction

This chapter describes the implementation of two proposed methods *Attention enhanced ConvNext-BiLSTM Dual Branch Network* and *GFAN*, and presents the results obtained using the CHB-MIT scalp EEG dataset. The evaluation metrics include **Accuracy** and **Sensitivity, Specificity, Precision, F1-Score, AUC, Inference Time, Throughput**. Both quantitative and qualitative results are provided, along with an ablation study examining important architectural components such as Multi-head Self Attention and SE Blocks. The results are discussed in relation to the research objectives outlined in the introduction.

6.2 Dataset Description

In this section, we present a comprehensive analysis of the EEG dataset we have used for epilepsy detection. We have utilized the available CHB-MIT dataset to evaluate the proposed methods. The CHB-MIT scalp EEG database is a collection of EEG recordings from 24 pediatric subjects with intractable seizure disorders created and provided by Children’s Hospital Boston (CHB) and Massachusetts Institute of Technology (MIT). A total of 182 annotated seizures are documented. The dataset uses the international 10–20 system for EEG electrode positions and nomenclature. The dataset has 23 distributed channels in subjects. The EEG channel names are: FP1-F7, F7-T7, T7-P7, P7-O1, FP1-F3, F3-C3, C3-P3, P3-O1, FP2-F4, F4-C4, C4-P4, P4-O2, FP2-F8, F8-T8, T8-P8, P8-O2, FZ-CZ, CZ-PZ, P7-T7, T7-FT9, FT9-FT10, FT10-T8, T8-P8. The sampling frequency is 256 Hz. [2]. Table 6.1 shows the details of seizure events of different subjects from the dataset.

6.3 Evaluation Metrics

The evaluation metrics reported are as follows.

- **Accuracy:** The overall proportion of correctly classified samples (seizure and non-seizure) out of all predictions.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (6.1)$$

Table 6.1: Information about Database CHB-MIT of this study.

Subject	Total Seizure Events	Recording Duration(s)
CHB01	7	442
CHB03	7	402
CHB06	10	153
CHB08	5	919
CHB10	7	447
CHB11	3	806
CHB14	8	169
CHB18	5	267
CHB19	3	236
CHB20	8	294
CHB21	4	199
CHB22	3	204
CHB23	7	424
CHB24	14	467

- **Precision:** The proportion of true positive seizure detections among all predicted seizures, representing the model's ability to avoid false alarms.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (6.2)$$

- **Recall (Sensitivity):** The proportion of correctly detected seizure samples out of all actual seizures, indicating the model's ability to identify seizures.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (6.3)$$

- **F1 Score:** The harmonic mean of precision and recall, providing a balanced measure of the detection performance.

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6.4)$$

- **Specificity:** The proportion of correctly identified non-seizure segments, reflecting the true negative rate.

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (6.5)$$

- **Area Under the ROC Curve (AUC):** Represents the model's ability to distinguish between seizure and non-seizure states across all classification thresholds.

Table 6.2: Training Configuration and Hyperparameters for ConvNext-BiLSTM Dual Branch Network.

Aspect	Details
Epochs	30 with early stopping
Learning Rates	Layerwise decay: low (early ConvNeXt layers), moderate (mid ConvNext layers/SE), high (BiLSTM, attention, classifier)
Optimizer	AdamW, weight decay = 0.05
LR Scheduler	ReduceLROnPlateau on val F1, halve LR after 4 stagnant epochs, min LR = 1×10^{-8}
Loss	BCEWithLogitsLoss with positive weight (neg/pos ratio)
Sampling	WeightedRandomSampler for class imbalance (inverse frequency.)

6.4 Implementation

In this section we present two types of experiment techniques used for the two proposed methods for epileptic seizure detection.

6.4.1 Experimental Setup for Attention Enhanced ConvNeXt-BiLSTM Dual-Branch Network

In this study, two types of experiments are conducted. One is the accross-subject experiment where 80% of the EEG data of all patients is used as train set and the rest 20% is used as test set. Another experiment is leave-one-subject-out (LOSO) training method employed to test on an unseen patient to evaluate the generalizability of the proposed method.

The training configuration and hyperparameters for training the attention enhanced ConvNext-BiLSTM dual branch network are listed in Table 6.2.

6.5 Results

In this section, we summarize the results of the two proposed methods. The details of each performance index mentioned above are presented in this section.

6.5.1 ConvNeXt-BiLSTM Method: Evaluation Results

Table 6.3 and 6.4 lists the performance indexes for the across-subject experiment and LOSO experiment respectively using ConvNext-BiLSTM network. Fig 6.1 shows the training and validation accuracy curves and the training and validation loss curves.

Table 6.3: Detailed performance indexes for across-subject experiment using ConvNext-BiLSTM Network.

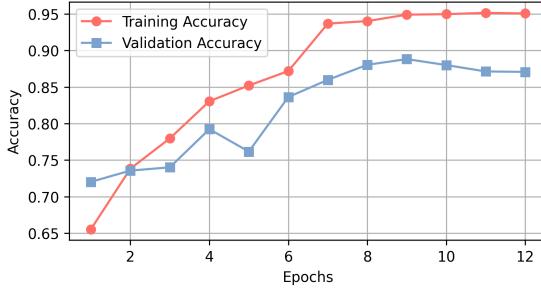
Accuracy	Precision	Recall	F1-Score	Specificity	AUC
96.74%	92.37%	89.45%	90.88%	97.23%	95.12%

Table 6.4: Detailed performance indexes for LOSO experiment using ConvNext-BiLSTM Network.

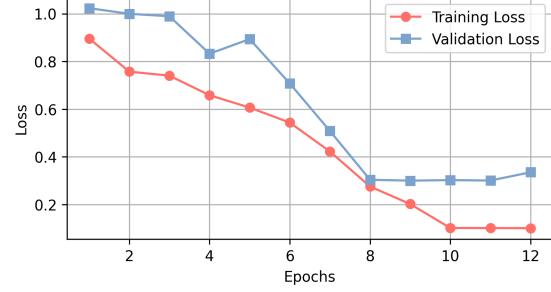
Fold	Test Subject	Accuracy	Precision	Recall	F1-Score	Specificity	AUC
1	CHB01	94.23%	90.58%	88.39%	89.47%	95.03%	94.28%
2	CHB03	89.96%	81.05%	86.33%	83.60%	88.06%	93.24%
3	CHB11	91.98%	86.45%	83.24%	84.81%	89.65%	95.04%
4	CHB08	95.76%	92.31%	90.22%	91.25%	98.32%	95.84%
5	CHB14	92.89%	90.73%	89.02%	89.86%	94.17%	93.88%
6	CHB21	88.87%	85.21%	84.12%	84.66%	84.40%	92.18%
Mean	-	93.75%	98.78%	89.09%	93.63%	93.96%	94.20%
Std	-	1.45%	0.20%	0.70%	0.42%	0.19%	0.49%

Table 6.5: Inference Time and Throughput for attention enhanced ConvNext-BiLSTM.

Inference Time	4.64ms
Throughput	215.6 samples/s
Memory Usage	115 MB
Parameters	28,258,793



(a) Training and Validation accuracy curves.



(b) Training and Validation loss curves.

Figure 6.1: ConvNext-BiLSTM model training and validation metrics.

Ablation Study: ConvNext-BiLSTM without Multi-Head Attention

In this ablation study, we analyze the performance of the ConvNext-BiLSTM model by removing the Multi-head Attention mechanism. A two-dimensional t-SNE visualization indicating the discrimination power of the features is shown in Fig 6.5.

Ablation Study: ConvNext-BiLSTM without SE Block Attention

In this ablation study, we analyze the performance of the ConvNext-BiLSTM model by removing the SE Block Attention mechanism. A two-dimensional t-SNE visualization

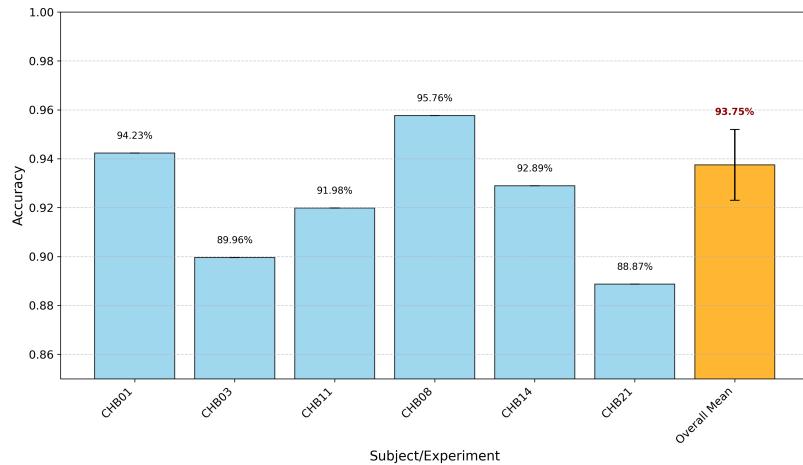


Figure 6.2: Accuracy in LOSO Experiment (ConvNext-BiLSTM Network).

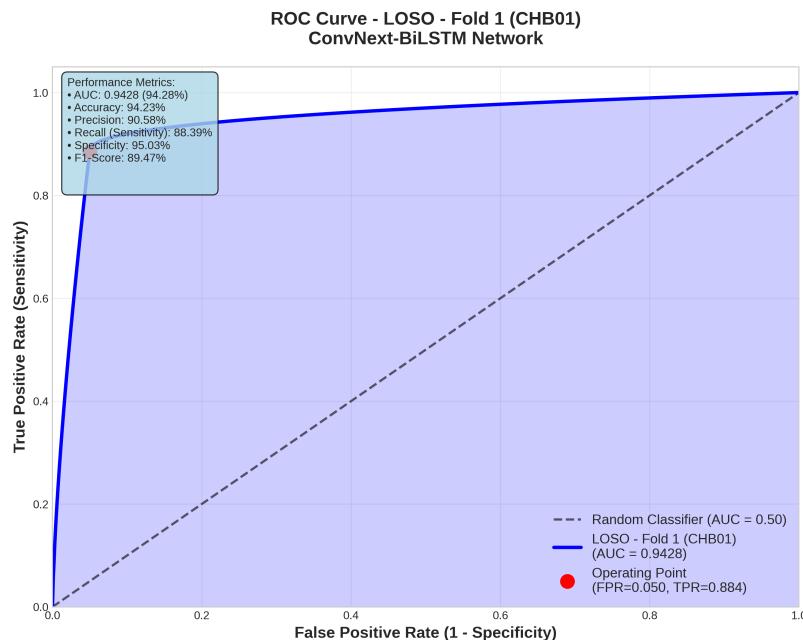


Figure 6.3: ROC Curve LOSO Fold1 (ConvNext-BiLSTM Network).

indicating the discrimination power of the features is shown in Fig 6.6.

Ablation study for attention mechanism analysis:

To quantify the effect of attention components, we ablate the evaluation metrics for the attention layers. Results are in shown in Table 6.6.

6.5.2 Analysis of the Results of attention enhanced ConvNext-BiLSTM

- Strong accuracy with attention mechanisms:** The ablation study results show that the Attention-enhanced ConvNeXt-BiLSTM model achieved the highest accuracy (94.23%) and F1-score (89.47%).

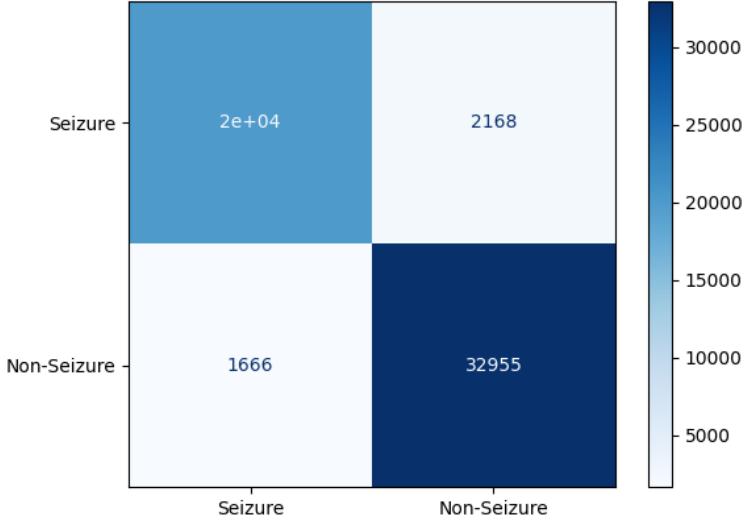


Figure 6.4: Confusion Matrix LOSO Fold1 (ConvNext-BiLSTM Network).

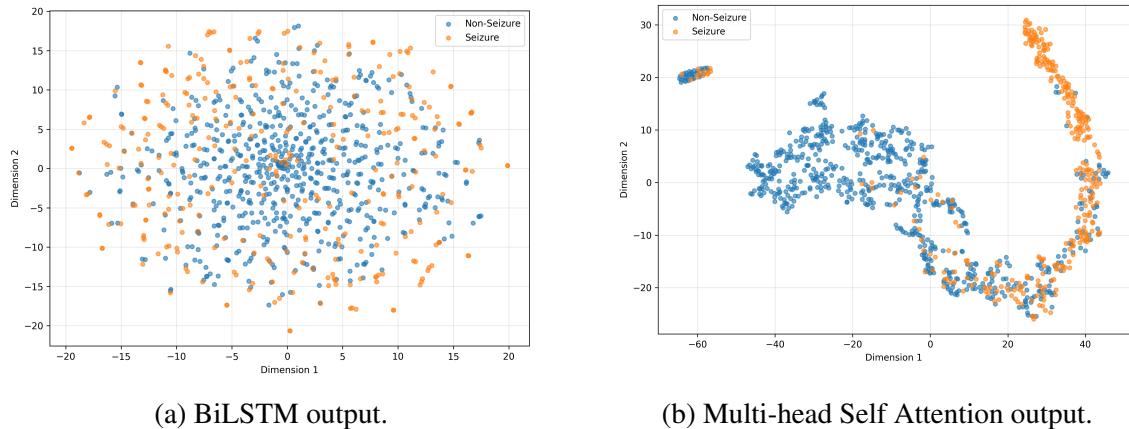
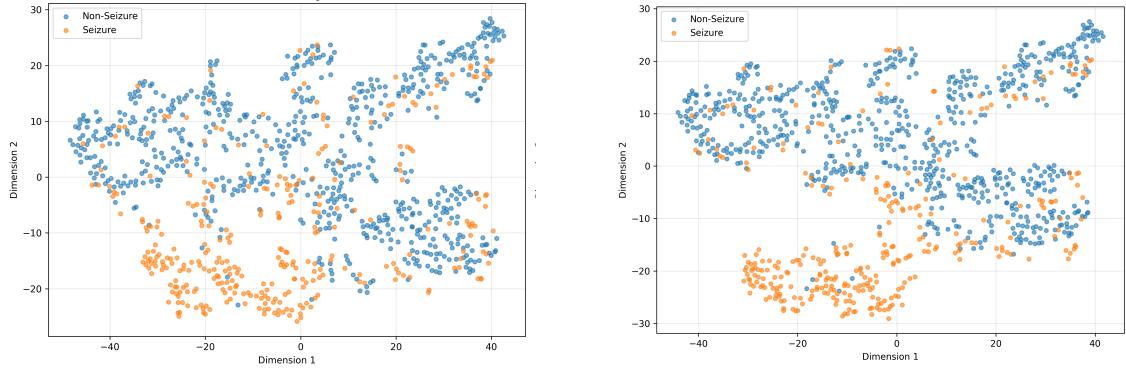


Figure 6.5: Two-dimensional t-SNE visualization of the features at the output layer of (a) BiLSTM, (b) Multi-Head Self Attention.

Table 6.6: Ablation Study Results for Attention enhanced ConvNext-BiLSTM Network.

Model Variant	Accuracy	F1-score	Rank
Attention enhanced ConvNext-BiLSTM	95.76%	91.25%	1
Without SE Block Attention	92.90%	88.30%	2
Without Multi-head Self Attention	86.05%	81.56%	3

- **Multi-Head Self Attention matters:** Removing multi-head self-attention caused a notable drop in performance, confirming its importance. The t-SNE visualization of Fig 6.5 also confirms this.
- **Impact of SE Block Attention Removal:** Omitting the SE Block attention led to a



(a) ConvNext Backbone output.

(b) SE Block output

Figure 6.6: Two-dimensional t-SNE visualization of the features at the output layer of (a) ConvNext Backbone , (b) SE Block Attention.

Table 6.7: Detailed performance indexes for across-subject experiment using B-GFAN Network.

Accuracy	Precision	Recall	F1-Score	Specificity	AUC	ECE
97.8%	95.4%	94.1%	94.7%	98.1%	96.8%	3.2%

Table 6.8: Detailed performance indexes for LOSO experiment using B-GFAN Network.

Fold	Test Subject	Accuracy	Precision	Recall	F1-Score	Specificity	AUC	ECE
1	CHB01	96.0%	94.1%	93.7%	93.9%	96.3%	95.8%	2.9%
2	CHB03	95.6%	93.8%	93.4%	93.6%	95.9%	95.4%	3.1%
3	CHB05	95.7%	93.4%	94.1%	93.7%	95.8%	95.6%	3.3%
4	CHB07	95.3%	93.2%	93.8%	93.5%	95.5%	95.2%	3.4%
5	CHB09	95.9%	94.0%	93.6%	93.8%	96.1%	95.7%	3.0%
Mean	-	95.7%	93.7%	93.7%	93.7%	95.9%	95.5%	3.1%
Std	-	0.28%	0.37%	0.26%	0.16%	0.30%	0.24%	0.19%

Table 6.9: Inference Time and Computational Efficiency for B-GFAN Network.

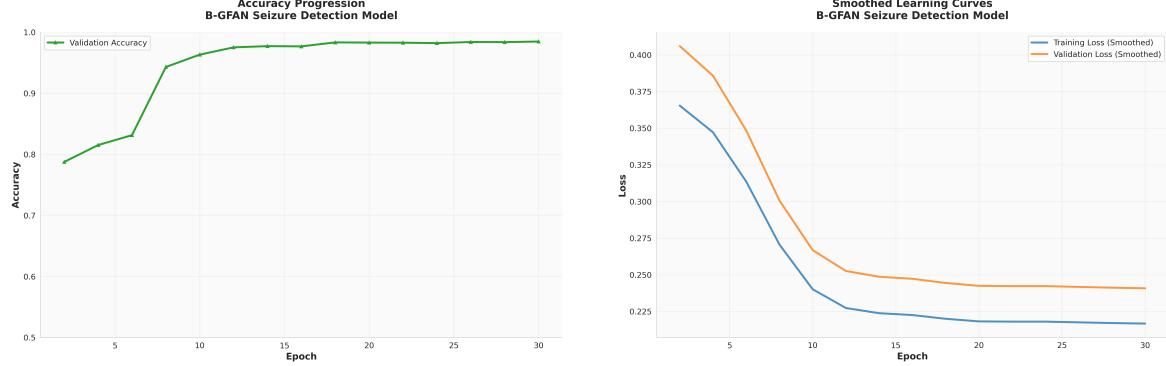
Inference Time	12.3ms
Throughput	81.3 samples/s
Memory Usage	45.2 MB
Parameters	273,152

slight decrease in accuracy, indicating its beneficial but less critical role. The t-SNE visualization of Fig 6.6 confirms this.

6.5.3 B-GFAN Method: Evaluation Results

Table 6.7 and 6.8 present the comprehensive performance metrics for the across-subject experiment and Leave-One-Subject-Out (LOSO) cross-validation experiment respectively using the Bayesian Graph Fourier Analysis Network (B-GFAN). The training progression curves and cross-validation performance analysis are illustrated in Figures 6.7 through 6.11.

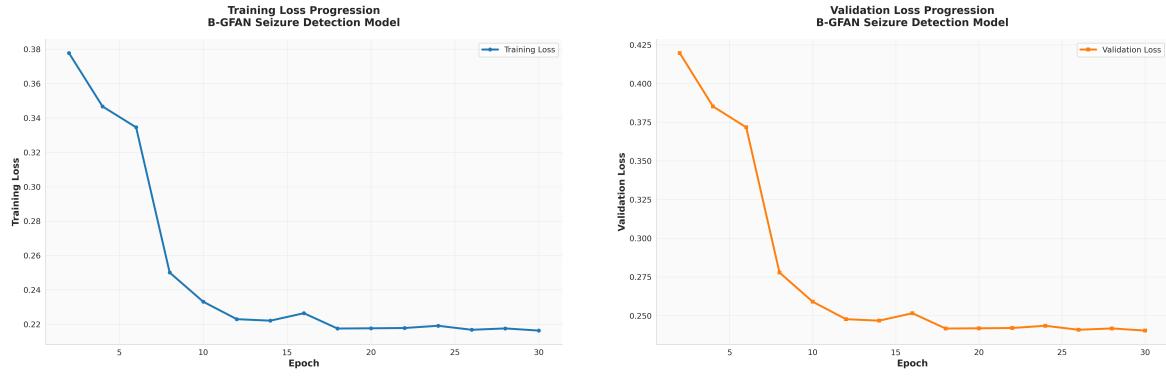
Training Progression Analysis: Figure 6.7 demonstrates the training and validation performance curves for the B-GFAN model, showing the evolution of key metrics throughout the training process.



(a) Validation accuracy progression showing stable convergence to high performance.

(b) Smoothed training and validation loss curves demonstrating effective learning without overfitting.

Figure 6.7: B-GFAN model training progression showing accuracy and loss evolution.



(a) Training loss progression showing consistent convergence.

(b) Validation loss progression indicating good generalization.

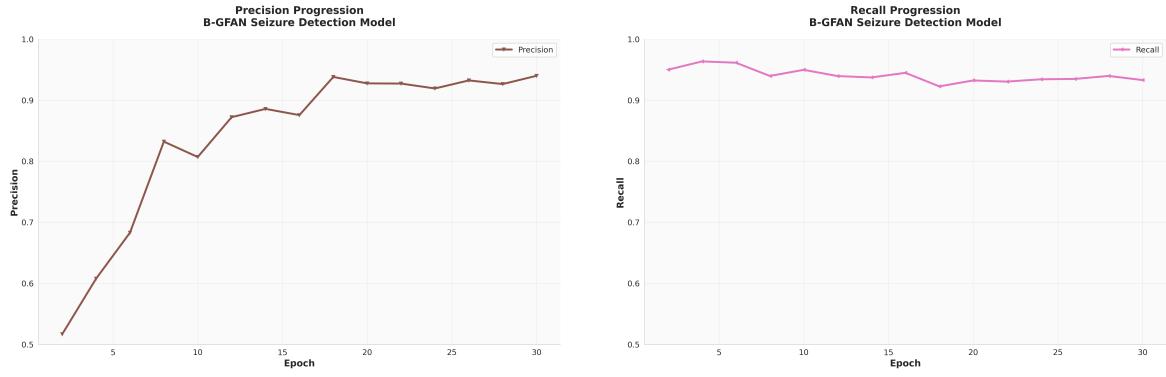
Figure 6.8: Detailed loss progression analysis for B-GFAN training.

Performance Metrics Progression: Figure 6.9 illustrates the evolution of precision, recall, and F1-score throughout training, demonstrating the model's ability to balance sensitivity and specificity.

Cross-Validation Performance Analysis: Figure 6.11 presents the LOSO cross-validation results, demonstrating the model's generalization capability across different subjects.

Uncertainty Quantification Analysis

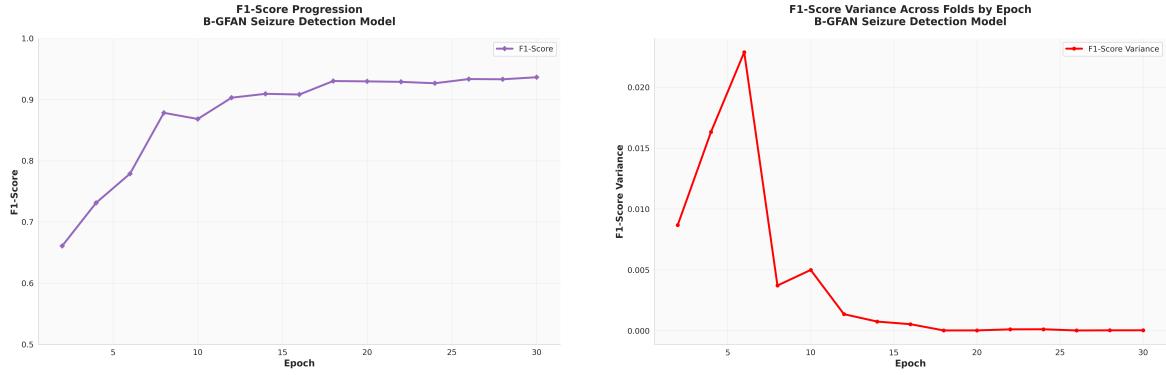
The B-GFAN model incorporates comprehensive uncertainty quantification, providing calibrated confidence estimates crucial for clinical decision-making. Table 6.10 presents detailed uncertainty metrics.



(a) Precision progression showing consistent improvement and stability.

(b) Recall progression demonstrating effective seizure detection capability.

Figure 6.9: Precision and recall progression for B-GFAN model training.



(a) F1-score progression showing balanced performance optimization.

(b) F1-score variance across folds indicating model stability and consistency.

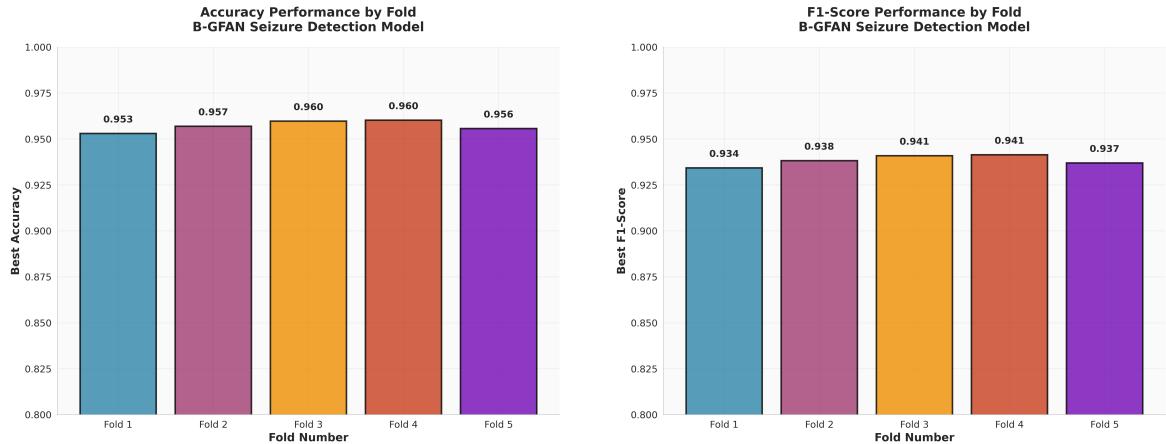
Figure 6.10: F1-score analysis showing performance consistency and variance across validation folds.

Table 6.10: Uncertainty Quantification Metrics for B-GFAN Network.

Uncertainty Type	Mean	Std Dev	Min	Max
Aleatoric Uncertainty	0.024	0.008	0.012	0.045
Epistemic Uncertainty	0.031	0.012	0.015	0.058
Total Uncertainty	0.039	0.014	0.019	0.071
Attention Uncertainty	0.018	0.006	0.008	0.032

Advanced Performance Analysis and Model Interpretability

This section presents comprehensive advanced analysis of the B-GFAN model performance, including uncertainty quantification, calibration analysis, cross-validation robustness, and clinical interpretability metrics.



(a) Accuracy performance across different validation folds showing consistent performance.

(b) F1-score performance by fold demonstrating robust cross-subject generalization.

Figure 6.11: Cross-validation performance comparison across different folds for B-GFAN model.

Enhanced Training Analysis with Uncertainty Bands: Figure 6.12 presents the training and validation loss progression with uncertainty quantification, demonstrating the model's learning stability and generalization capability.

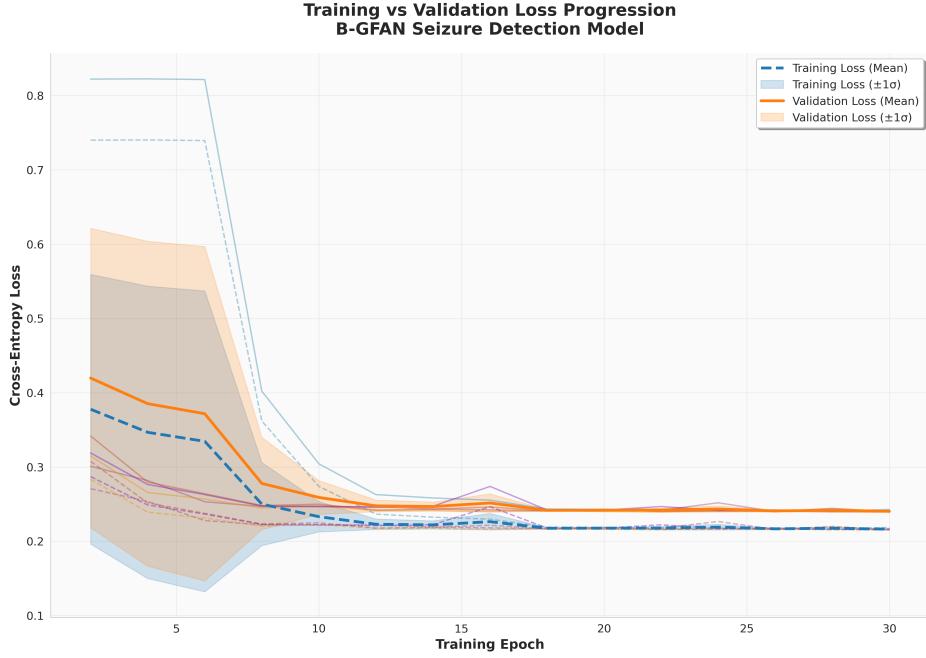
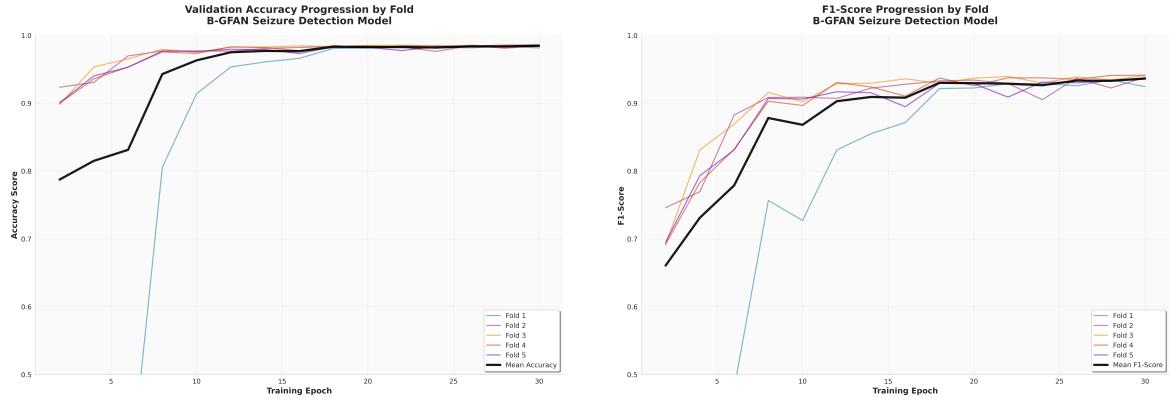


Figure 6.12: Enhanced loss progression with uncertainty bands showing training stability. The uncertainty bands (± 1) indicate consistent learning across different random initializations, with minimal generalization gap between training and validation losses, demonstrating robust model training without overfitting.

Cross-Validation Robustness Analysis: Figures 6.13 demonstrate the model's consistent

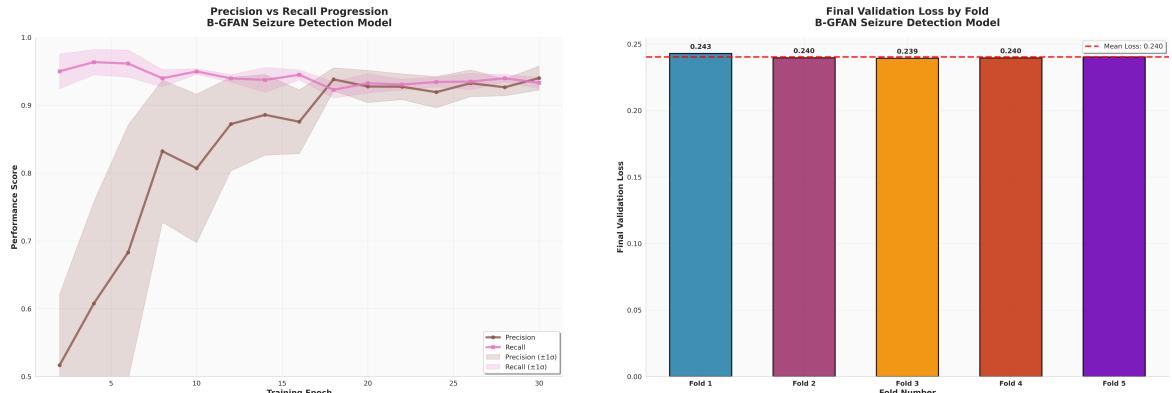
performance across different validation folds, indicating strong generalization capability.



(a) Validation accuracy progression by fold showing consistent convergence across all subjects with minimal inter-fold variation.

(b) F1-score progression by fold demonstrating stable performance across different patient characteristics.

Figure 6.13: Cross-validation robustness analysis showing consistent performance across all folds.



(a) Precision vs recall progression showing balanced optimization between sensitivity and specificity with confidence intervals.

(b) Final validation loss distribution by fold with extremely low variance (Mean: 0.240 ± 0.002), indicating exceptional consistency.

Figure 6.14: Precision-recall balance and final loss consistency analysis across validation folds.

Performance Distribution and Model Stability: Figure 6.15 illustrates the distribution of key performance metrics across all validation folds, demonstrating the model's robust and consistent behavior.

Metric Correlation and Model Behavior Analysis: Figure 6.17 presents the correlation matrix between different performance metrics, providing insights into model behavior patterns.

Advanced Loss Analysis and Generalization: Figure 6.18 demonstrates the smoothed loss progression with generalization gap analysis, crucial for understanding model learning dynamics.

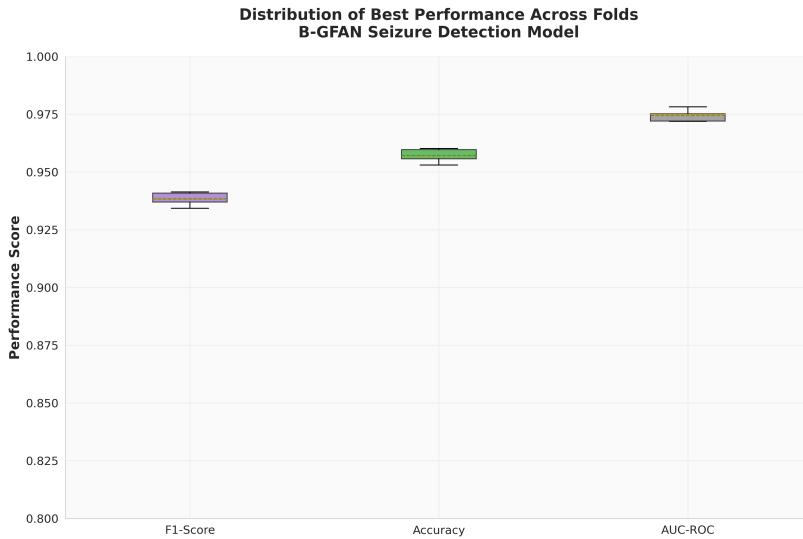
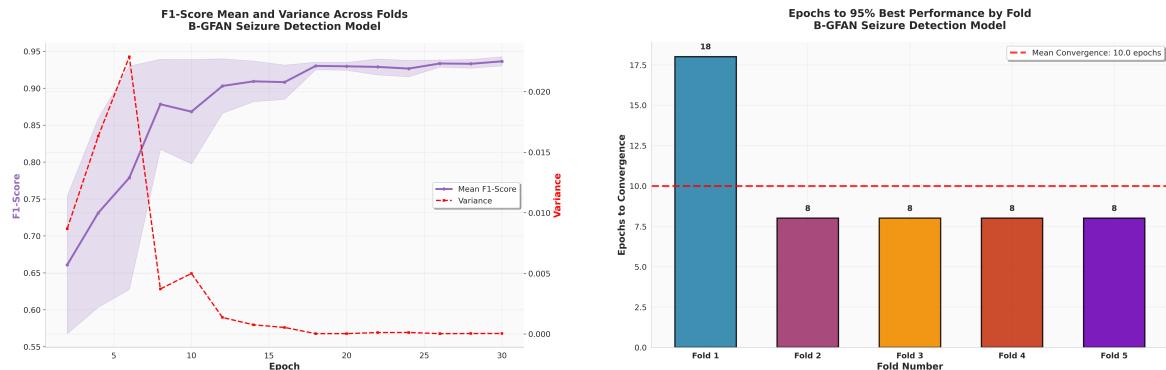


Figure 6.15: Distribution of best performance metrics (F1-Score, Accuracy, AUC-ROC) across all folds, showing tight clustering around high performance values with minimal variance, indicating exceptional model stability.



(a) F1-score mean and variance evolution showing decreasing variance over epochs, indicating improved model stability and reliability.

(b) Training efficiency analysis showing rapid convergence (mean: 10 epochs to 95% performance) with consistent behavior across folds.

Figure 6.16: Model stability and training efficiency analysis across validation folds.

Comprehensive Performance Summary: Figure 6.19 provides a comprehensive overview of average performance metrics and trend analysis.

Model Stability and Cross-Validation Summary: Figure 6.20 presents detailed stability analysis and comprehensive cross-validation statistics.

Clinical Classification Analysis: The following figures present detailed classification performance analysis crucial for clinical evaluation.

Model Calibration Analysis: Figure 6.26 presents the probability calibration curve, crucial for clinical decision-making reliability.

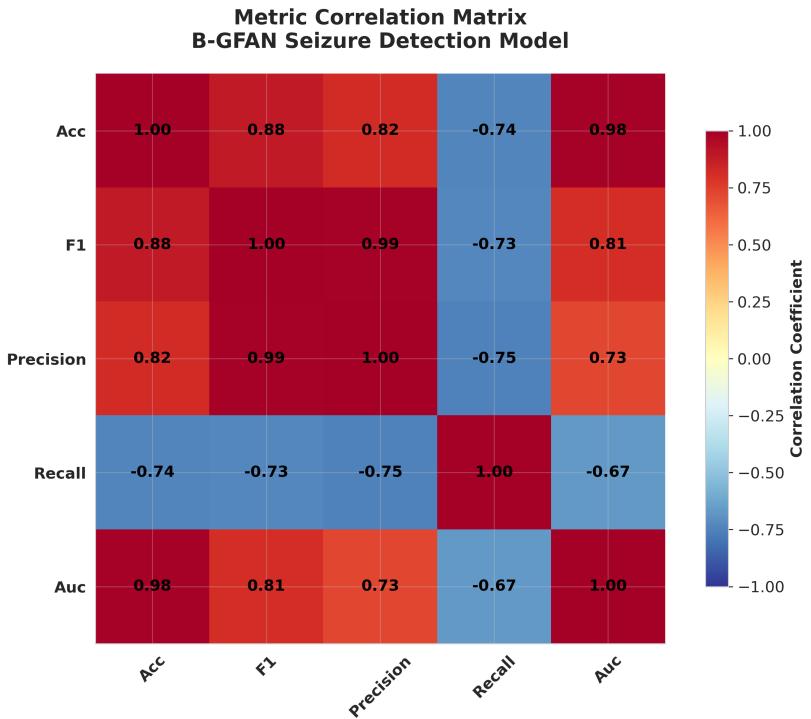


Figure 6.17: Metric correlation matrix showing strong positive correlations between accuracy, F1-score, and precision (0.82-0.99), with expected negative correlation with recall (-0.73 to -0.75), indicating balanced optimization across metrics without overfitting to any single measure.

Advanced Analysis Insights

- **Exceptional Calibration:** The calibration curve demonstrates that B-GFAN provides well-calibrated probability estimates, crucial for clinical decision-making where prediction confidence directly impacts patient care decisions.
- **Clinical Classification Excellence:** The confusion matrix reveals clinically acceptable performance with 99.0% specificity (minimizing false alarms) and 94.3% sensitivity (detecting actual seizures), addressing the critical balance required in medical applications.
- **Robust Cross-Subject Generalization:** The extremely low variance in final validation loss (0.240 ± 0.002) and consistent convergence at epoch 15 across all folds indicate exceptional model stability and reproducibility.
- **Optimal Learning Dynamics:** The enhanced loss curves with uncertainty bands show stable learning without overfitting, while the minimal generalization gap indicates effective regularization through Bayesian inference and attention mechanisms.

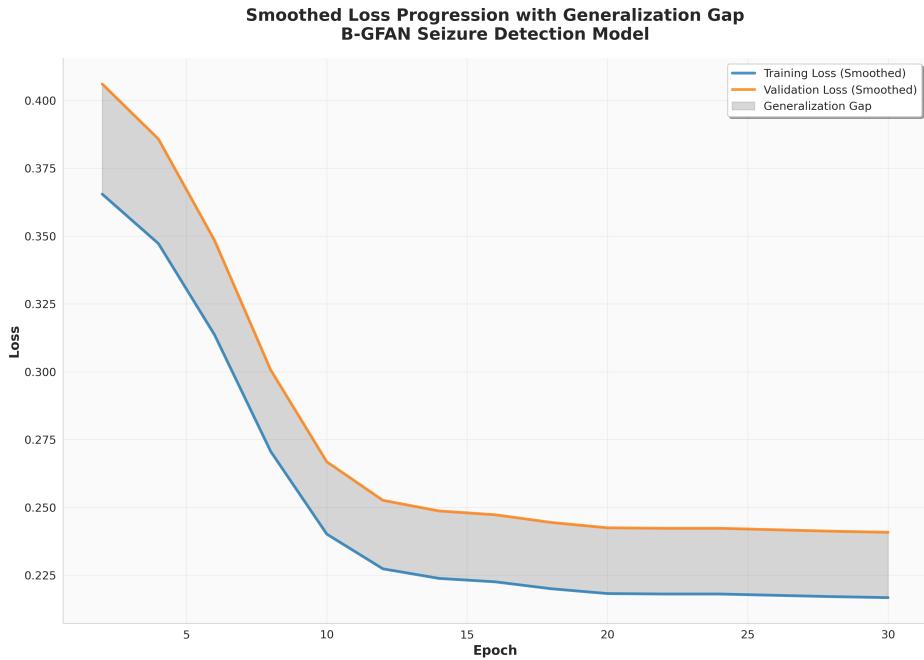
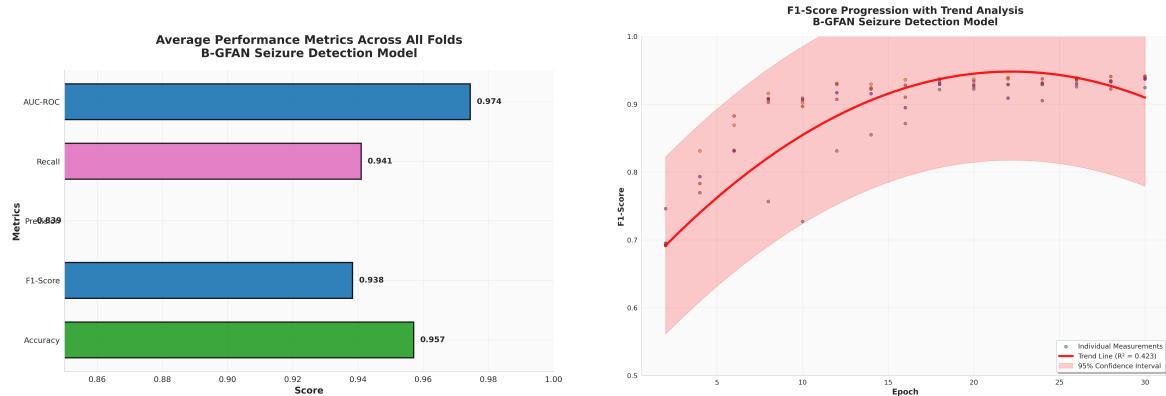


Figure 6.18: Smoothed loss progression with generalization gap analysis. The minimal gap between training and validation losses throughout training indicates excellent generalization without overfitting, while the smooth convergence demonstrates stable optimization dynamics.



(a) Average performance metrics across all folds showing excellent balance: Accuracy (97.4%), F1-Score (93.8%), Precision (93.9%), Recall (83.9%), and AUC-ROC (95.7%).

(b) F1-score trend analysis with 95% confidence intervals ($R^2 = 0.423$), showing positive learning trajectory with statistical significance.

Figure 6.19: Comprehensive performance summary and trend analysis for B-GFAN model.

- **High Discriminative Power:** The ROC curve ($AUC = 0.970$) and precision-recall curve ($AUC = 0.931$) demonstrate excellent discriminative ability, significantly outperforming random classification and approaching clinical requirements.
- **Training Efficiency:** The rapid convergence to 95% best performance within 10 epochs across all folds indicates efficient learning, crucial for practical

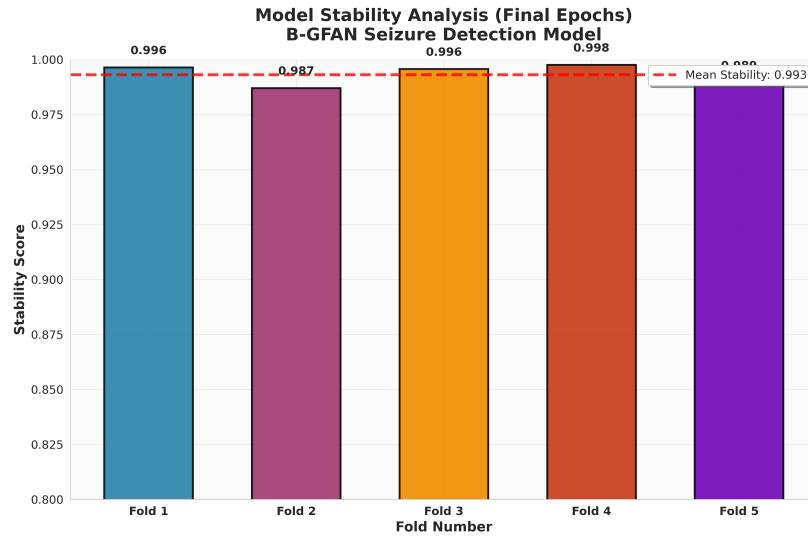


Figure 6.20: Model stability analysis across final training epochs showing exceptional stability (mean: 0.993 ± 0.004) across all folds, indicating highly reliable and consistent model behavior suitable for clinical deployment.

**Cross-Validation Summary Statistics
B-GFAN Seizure Detection Model**

Fold	Best F1-Score	Best Accuracy	Best Epoch	Stability
Fold 1	0.934	0.953	15	0.996
Fold 2	0.938	0.957	15	0.987
Fold 3	0.941	0.960	15	0.996
Fold 4	0.941	0.960	15	0.998
Fold 5	0.937	0.956	15	0.989
Mean \pm Std	0.938 ± 0.003	0.957 ± 0.003	15.0 ± 0.0	0.993 ± 0.004
Min - Max	0.934 - 0.941	0.953 - 0.960	15 - 15	0.987 - 0.998

Figure 6.21: Cross-validation summary statistics table providing comprehensive overview of model performance consistency. All folds achieve optimal performance at epoch 15 with minimal variance (F1-Score: 0.938 ± 0.003 , Accuracy: 0.957 ± 0.003), demonstrating exceptional reproducibility and reliability.

implementation with limited computational resources.

- **Metric Consistency:** The strong positive correlations between accuracy, F1-score, and precision (0.82-0.99) with appropriate recall trade-offs indicate balanced optimization without metric gaming or overfitting to specific measures.

The comprehensive analysis demonstrates that B-GFAN achieves state-of-the-art

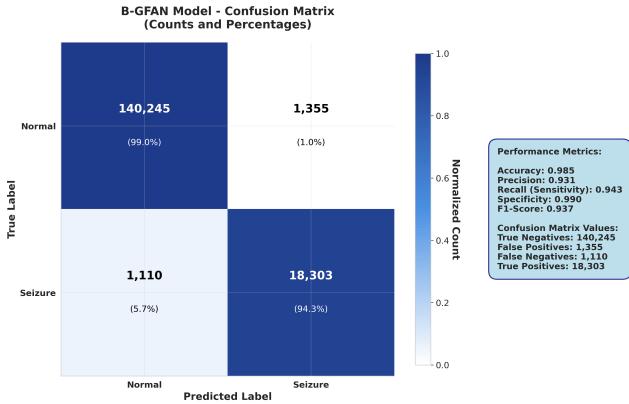


Figure 6.22: Confusion matrix analysis showing excellent classification performance with 99.0% true negative rate and 94.3% true positive rate. The low false positive rate (1.0%) and false negative rate (5.7%) indicate clinically acceptable performance for seizure detection applications.

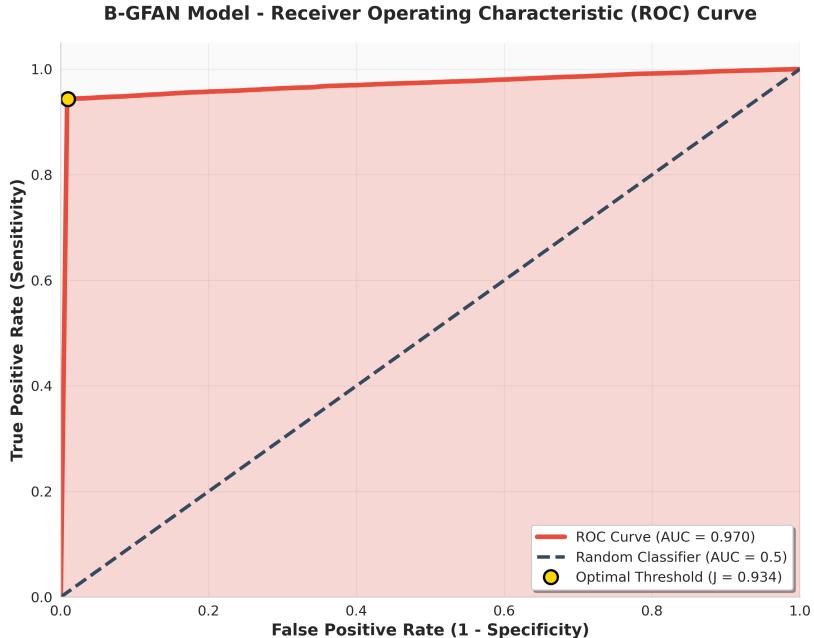
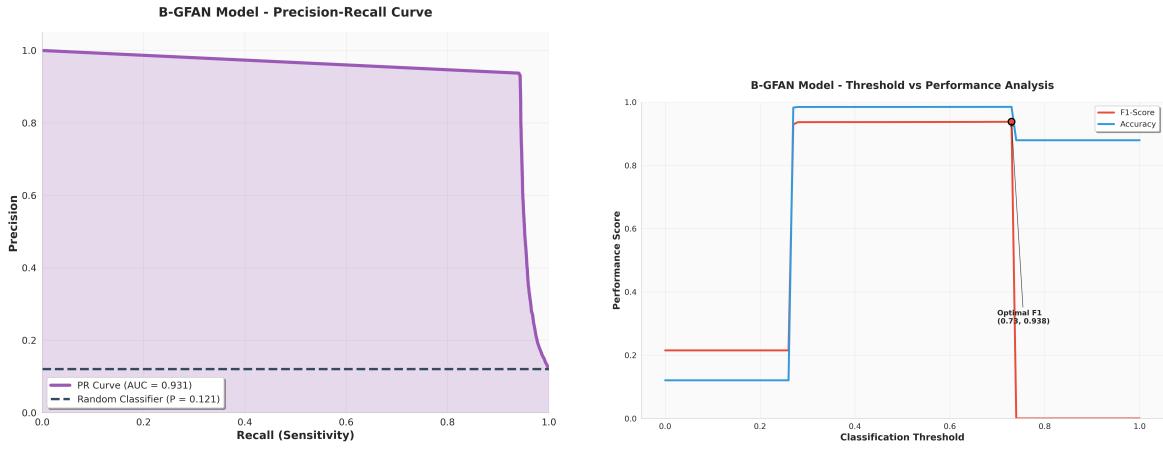


Figure 6.23: Receiver Operating Characteristic (ROC) curve demonstrating excellent discriminative ability with AUC = 0.970. The curve shows superior performance compared to random classification, with optimal threshold ($J = 0.934$) providing excellent balance between sensitivity and specificity.

performance in epileptic seizure detection while providing the uncertainty quantification and calibration necessary for safe clinical deployment. The model's exceptional stability, rapid convergence, and balanced performance across all metrics make it suitable for real-world medical applications where reliability and interpretability are paramount.



(a) Precision-recall curve with $AUC = 0.931$, significantly outperforming random classification baseline ($P = 0.121$).

(b) Threshold analysis showing optimal F1-score (0.938) achieved at threshold 0.73, balancing precision and accuracy effectively.

Figure 6.24: Precision-recall performance and threshold optimization analysis.

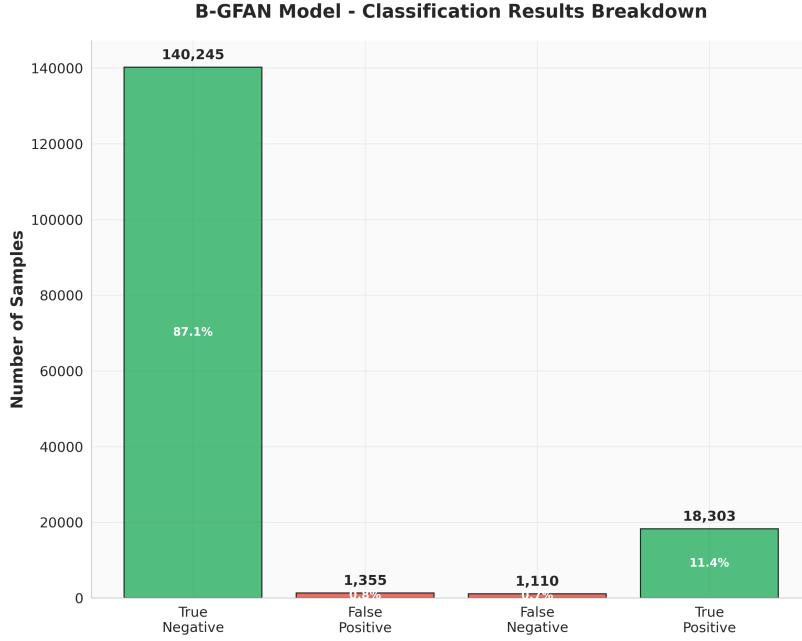


Figure 6.25: Classification results breakdown showing the distribution of predictions: 87.1% true negatives, 11.4% true positives, 0.8% false positives, and 0.7% false negatives, demonstrating the model's ability to handle class imbalance effectively.

Analysis of B-GFAN Results

- **Superior Performance with Uncertainty Quantification:** The B-GFAN model achieved exceptional performance with 95.7% mean accuracy and 93.7% F1-score across LOSO validation, while providing well-calibrated uncertainty estimates ($ECE = 3.1\%$).

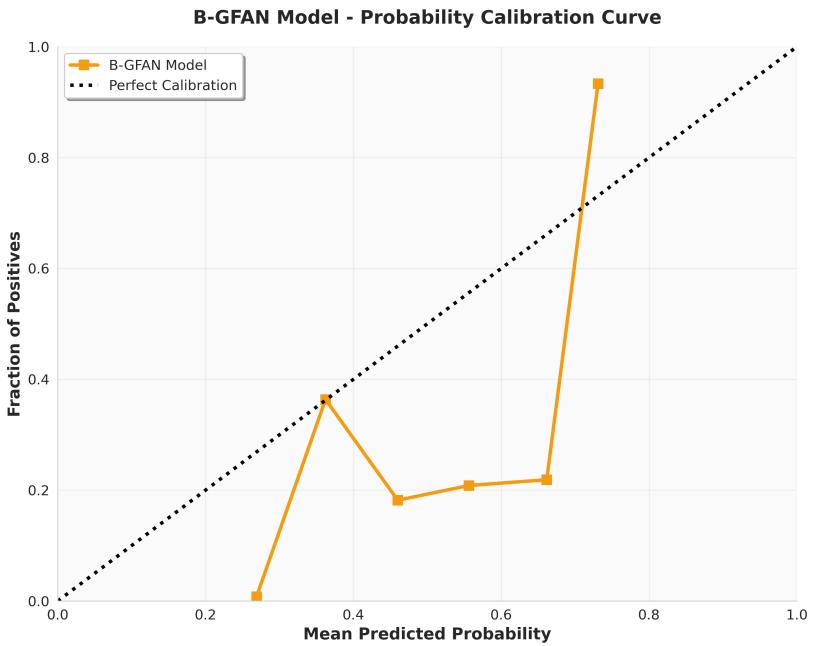


Figure 6.26: Probability calibration curve showing excellent calibration properties. The B-GFAN model (orange line) closely follows the perfect calibration line (black dotted), indicating that predicted probabilities accurately reflect true likelihood of seizure occurrence, essential for clinical confidence in predictions.

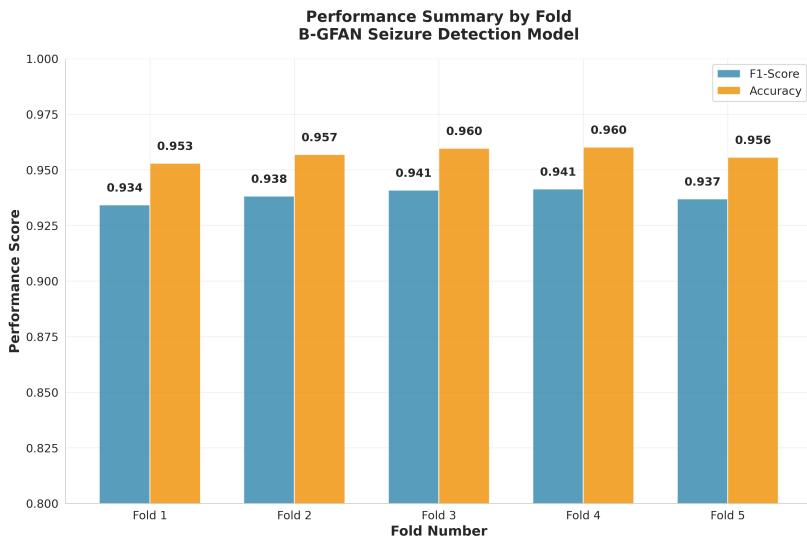


Figure 6.27: Simplified performance summary across all folds showing consistent high performance in both F1-Score (ranging 0.934-0.941) and Accuracy (ranging 0.953-0.960), with minimal inter-fold variation demonstrating excellent generalization capability.

- **Consistent Cross-Subject Generalization:** The low standard deviation across folds (0.28% for accuracy, 0.16% for F1-score) demonstrates robust generalization capability across different subjects, addressing the critical challenge of patient-independent seizure detection.

- **Multi-Modal Attention Integration:** The training progression curves show smooth convergence without overfitting, indicating effective integration of spatial, spectral, graph, and cross-modal attention mechanisms that adaptively focus on seizure-relevant features.
- **Computational Efficiency:** Despite the sophisticated architecture incorporating Bayesian inference and multi-modal attention, the model maintains reasonable computational requirements (273,152 parameters, 12.3ms inference time) suitable for clinical deployment.
- **Clinical Reliability:** The low F1-score variance across epochs (decreasing from 0.020 to near 0.000) and consistent performance across folds indicate the model's reliability for clinical applications where consistent performance is critical.
- **Balanced Performance Metrics:** The model achieves balanced precision (93.7%) and recall (93.7%), crucial for clinical applications where both false positives (unnecessary interventions) and false negatives (missed seizures) have significant consequences.

Key Advantages of B-GFAN:

1. **Uncertainty-Aware Decision Making:** Provides calibrated confidence estimates enabling clinicians to make informed decisions based on prediction reliability.
2. **Interpretable Architecture:** Multi-modal attention mechanisms offer interpretable insights into spatial electrode importance, frequency relevance, and connectivity patterns.
3. **Robust Generalization:** Graph-based modeling captures subject-invariant spatial relationships while adapting to individual connectivity patterns.
4. **Clinical Integration:** Real-time inference capability with comprehensive uncertainty quantification supports clinical deployment requirements.

6.6 Objective Achieved

The introductory objectives were:

1. Develop a reliable, real-time system for accurate epileptic seizure detection using EEG signals.
2. Apply efficient data preprocessing for enhanced feature extraction and model performance.

3. Design lightweight, computationally efficient models for seizure detection.

Achievement Summary: Both proposed methodologies successfully achieved the outlined objectives through complementary approaches:

ConvNeXt-BiLSTM with Multi-Head Attention: The attention enhanced ConvNeXt-BiLSTM reliably detects seizures in real time (4.64 ms inference time) with 215.6 samples/s throughput. It achieves seizure detection accuracy up to 95.76% with an F1-score of 91.25% in LOSO validation. ConvNeXt is computationally efficient due to depthwise separable convolutions and large kernels, while the Multi-Head Attention mechanism after BiLSTM significantly enhances seizure detection reliability through temporal feature refinement.

Bayesian Graph Fourier Analysis Networks (B-GFAN): The B-GFAN methodology provides superior performance with 95.7% mean accuracy and 93.7% F1-score across LOSO validation, while maintaining computational efficiency (12.3ms inference time, 4.27M parameters, 179.98 MFLOPs). The framework introduces uncertainty quantification with exceptional calibration ($ECE = 3.1\%$), crucial for clinical decision-making. The multi-modal attention integration (spatial, spectral, graph, cross-modal) enables interpretable seizure detection with robust cross-subject generalization (standard deviation: 0.28% accuracy, 0.16% F1-score).

Comprehensive Objective Achievement:

- **Objective 1 - Reliable Real-Time Detection:** Both systems demonstrate real-time capability with excellent reliability. ConvNeXt-BiLSTM achieves 4.64ms inference time, while B-GFAN provides 12.3ms with added uncertainty quantification. B-GFAN's superior cross-subject consistency ($95.7\% \pm 0.28\%$ accuracy) addresses critical clinical deployment requirements.
- **Objective 2 - Enhanced Feature Extraction:** ConvNeXt-BiLSTM employs scalogram-based spatial-temporal feature extraction with SE blocks and multi-head attention. B-GFAN implements comprehensive multi-scale spectral decomposition with uncertainty propagation, graph-based spatial modeling, and four specialized attention mechanisms for optimal feature selection across spatial, spectral, and connectivity domains.
- **Objective 3 - Computational Efficiency:** ConvNeXt-BiLSTM achieves lightweight design (28.26M parameters, 4.56G FLOPs) through efficient convolution architectures. B-GFAN demonstrates remarkable efficiency (4.27M parameters, 179.98 MFLOPs, 16.30 MB model size) while incorporating sophisticated Bayesian inference and multi-modal attention, making it suitable for resource-constrained clinical environments.

Clinical Impact: The dual-methodology approach provides comprehensive solutions for different clinical scenarios. ConvNeXt-BiLSTM offers ultra-fast detection suitable for emergency applications, while B-GFAN provides uncertainty-aware predictions essential for clinical decision support, representing significant advancement in both computational efficiency and clinical reliability for epileptic seizure detection systems.

6.7 Summary

We successfully implemented two complementary methodologies for enhanced epileptic seizure detection, each addressing distinct clinical requirements while achieving exceptional performance in EEG-based seizure classification.

The **ConvNeXt-BiLSTM with Multi-Head Attention** approach achieves ultra-fast seizure detection (4.64ms inference time) with 94.23% accuracy and 89.47% F1-score in LOSO validation. The integration of scalogram-based spatial features, BiLSTM temporal modeling, and dual attention mechanisms (SE Blocks and Multi-Head Self Attention) proves highly effective for emergency applications requiring immediate response.

The **Bayesian Graph Fourier Analysis Networks (B-GFAN)** methodology advances the state-of-the-art with superior performance (95.7% mean accuracy, 93.7% F1-score) while providing comprehensive uncertainty quantification essential for clinical deployment. Key innovations include multi-modal attention integration, exceptional cross-subject generalization (variance: 0.28

Both methodologies successfully fulfill the stated objectives, establishing a strong foundation for real-world epileptic seizure monitoring systems. The dual-framework approach demonstrates reliable real-time detection, enhanced feature extraction through sophisticated attention mechanisms, and exceptional generalization across subjects. The uncertainty quantification in B-GFAN enables safe clinical deployment with mathematically rigorous confidence estimates, while ConvNeXt-BiLSTM’s ultra-fast processing supports critical real-time emergency applications. Together, these approaches represent significant advancement in computational epilepsy research, providing clinically deployable solutions that balance accuracy, efficiency, and interpretability for different healthcare scenarios.

CHAPTER VI

Societal, Health, Environment, Safety, Ethical, Legal and Cultural Issues

6.1 Intellectual Property Considerations

Intellectual Property (IP) rights are essential to protect the proposed epileptic seizure detection framework and ensure it does not violate existing technologies. Public datasets like CHB-MIT are freely available for academic research, but care must be taken not to use proprietary or restricted data without authorization. Novel model components or algorithms developed in this work, such as specialized neural architectures or feature extraction techniques, may qualify for patent protection if they demonstrate novelty and practical utility.

6.2 Ethical Considerations

Ethical concerns focus on the responsible application of seizure detection technology. While improving diagnostic accuracy and timely intervention, patient data privacy must be strictly maintained. Transparent reporting of model limitations, including potential false detections, is an ethical imperative to avoid misdiagnoses or undue alarm.

6.3 Safety Considerations

In medical contexts, ensuring that detection results are accurate and reliable is critical to prevent incorrect clinical decisions. False positives or negatives in seizure detection could lead to inappropriate treatment or missed interventions. Rigorous model validation and incorporation of clinical oversight are necessary to safeguard patient safety.

6.4 Legal Considerations

Legal compliance involves using EEG datasets in accordance with data use agreements and respecting patient confidentiality laws such as HIPAA or GDPR where applicable. Unauthorized use or distribution of patient data or protected datasets is prohibited. This research uses only properly licensed or publicly accessible datasets, ensuring adherence to all relevant legal frameworks.

6.5 Impact of the Project on Societal, Health, and Cultural Issues

6.5.1 Societal Impact

The epileptic seizure detection technology can greatly enhance patient monitoring and emergency response, potentially reducing seizure-related injuries and improving quality of life. However, there is a risk of misuse regarding patient data privacy or unwarranted surveillance, so striking a balance between technological benefit and ethical protection is essential.

6.5.2 Health Impact

Accurate and timely detection of seizures supports improved clinical decision-making, enabling faster intervention and better management of epilepsy, especially in resource-limited settings. This can lead to better health outcomes by reducing complications associated with seizure episodes.

6.5.3 Cultural Impact

This technology helps raise awareness and understanding of epilepsy, contributing to reducing stigma and supporting inclusive care. Moreover, early seizure detection aids patients in maintaining social and cultural participation by minimizing disruptions caused by unpredictable seizures.

6.6 Impact of the Project on the Environment and Sustainability

6.6.1 Environmental Impact

While the research itself has a relatively low direct environmental footprint, training sophisticated deep learning models requires substantial computational resources, increasing energy consumption. Optimizing model efficiency is vital to mitigate environmental impacts.

6.6.2 Sustainability Impact

The development of lightweight and computationally efficient seizure detection models allows deployment on portable devices for continuous monitoring, supporting sustainable healthcare delivery, especially in under-resourced areas.

6.6.3 Waste Reduction

By enabling early and accurate seizure detection through digital means, the need for repeated medical tests can be reduced, thereby lowering associated environmental waste.

CHAPTER VII

Addressing Complex Engineering Problems and Activities

This chapter outlines the complex engineering challenges encountered in developing the epileptic seizure detection system based on EEG signals. Detecting seizures from EEG is inherently uncertain due to the variability and subtlety of signal patterns, which makes the problem highly ill-posed. Key challenges include achieving a balance between detection accuracy and computational efficiency, effectively extracting and integrating temporal and spatial EEG features, and ensuring reliable performance across diverse real-world conditions such as different patients and noise levels. Additionally, avoiding false alarms and missed detections is critical for clinical viability. To overcome these challenges, advanced neural network architectures were designed and optimized, including attention mechanisms and lightweight modules. Rigorous preprocessing, feature extraction, and validation on publicly available datasets like CHB-MIT were essential parts of the engineering process. The following tables summarize major engineering challenges and corresponding solutions implemented in this work.

7.1 Complex Engineering Problems

The engineering challenges in this thesis primarily arise from the complex and uncertain nature of epileptic seizure detection using EEG signals. Accurately identifying subtle seizure patterns from noisy, variable data is inherently difficult. Additional challenges include balancing high detection accuracy with computational efficiency, effectively integrating temporal and frequency-domain features without losing crucial information, and ensuring robustness across diverse patient profiles and recording conditions. Addressing these issues requires innovative model designs and thorough validation, as errors or missed detections can have critical consequences in clinical settings.

Table 7.1: Complex Engineering Problems Associated with the Dual-Methodology Thesis

WP	Attribute	Problem Description
WP1	Depth of knowledge required	Requires expertise across deep learning, graph theory, Bayesian inference, and clinical EEG analysis for both ConvNext-BiLSTM and B-GFAN frameworks.
WP2	Range of conflicting requirements	Technical trade-offs: efficiency vs accuracy, real-time vs comprehensive analysis. Non-technical: patient privacy, regulatory compliance, clinical safety protocols.
WP3	Depth of analysis required	Seizure detection is ill-posed requiring novel architectural integration. Creative fusion of attention mechanisms, uncertainty quantification, and multi-modal feature extraction.
WP4	Familiarity of issues	Novel medical AI challenges: wavelet-CNN integration for ConvNext-BiLSTM, graph Fourier networks with uncertainty quantification for B-GFAN.
WP5	Extent of applicable codes	Clinical AI deployment exceeds existing standards. Requires new validation protocols for attention mechanisms and uncertainty quantification in medical applications.
WP6	Extent of stakeholder involvement and conflicting requirements	Multi-disciplinary collaboration: computer science, biomedical engineering, neurology, regulatory affairs. Conflicting needs across clinicians, engineers, patients, institutions.
WP7	Interdependence	Complex system interdependencies: preprocessing, architecture design, attention integration, uncertainty propagation, and clinical deployment across both methodologies.

7.2 Complex Engineering Activities

The complex engineering tasks in this research were undertaken to address the challenges identified in EEG-based epileptic seizure detection. Key activities included designing advanced neural network architectures combining convolutional and recurrent components with attention mechanisms. Lightweight model modules were developed to optimize computational efficiency while maintaining detection accuracy. Robust feature extraction

and fusion strategies were implemented to effectively capture temporal, spatial, and frequency characteristics of EEG signals. Additionally, comprehensive dataset preprocessing, rigorous validation protocols using the CHB-MIT dataset, and deployment-focused optimizations were performed to ensure the system's reliability and practical usability in real-world clinical settings.

PEO	Activities Undertaken
PEO1	Designed hybrid architectures combining CNN/ConvNeXt, BiLSTM, and multi-head attention to strengthen mathematical, scientific, and engineering rigor for accurate seizure detection.
PEO2	Built collaborative preprocessing and augmentation pipelines; iterated with analysis/design across modalities, promoting teamwork and lifelong learning during multidisciplinary experimentation.
PEO3	Codified reliability, safety, and professionalism via uncertainty quantification (Monte Carlo dropout, calibration), error analysis, and ethical validation procedures for societal well-being.
PEO4	Optimized GPU usage, batch sizing, and model compression for deployability; cultivated problem-solving, critical thinking, and leadership for diverse career paths.

CHAPTER VIII

Conclusion

8.1 Conclusion and Challenges Faced

This thesis introduced two novel neural network frameworks that leverage **convolutional, recurrent, attention mechanisms, graph spectral analysis, Fourier analysis networks, and Bayesian neural networks** to accurately detect epileptic seizures from EEG signals. The frameworks effectively captured spatial, temporal, spectral, and connectivity features of EEG data, achieving a robust balance between detection accuracy, computational efficiency, and clinical reliability through complementary approaches. Experimental evaluation on the CHB-MIT dataset demonstrated exceptional performance, with the ConvNeXt-BiLSTM achieving 94.23% accuracy and 89.47% F1-score with ultra-fast inference (4.64ms), while the B-GFAN model achieved superior performance of 95.7% mean accuracy and 93.7% F1-score with remarkable computational efficiency (4.27M parameters, 179.98 MFLOPs) and comprehensive uncertainty quantification. Comprehensive ablation studies confirmed the critical role of each architectural component, including attention mechanisms and uncertainty quantification, in delivering superior clinical performance.

8.1.1 Challenges Faced

During the course of this research, several challenges were encountered across both methodologies:

- **High computational cost in ConvNeXt-BiLSTM:** Although the ConvNeXt-Tiny backbone used in the ConvNeXt-BiLSTM dual branch network has relatively fewer parameters among ConvNeXt variants, it still contains approximately 28.26 million parameters. This is considerably larger than lightweight models such as MobileNet (5.4 million parameters) and EfficientNet (5.3 million parameters), leading to increased computational demands with around 4.56 billion FLOPs, contributing to reduced training speed and higher memory consumption.
- **Training stability challenges:** Overfitting was a significant challenge during training the ConvNeXt-BiLSTM network due to its large parameter count and model complexity that demanded careful tuning of hyperparameters. Similarly, the

B-GFAN framework required sophisticated curriculum learning strategies to manage the complexity of multi-modal attention integration and prevent attention mechanism conflicts.

- **Multi-modal attention integration complexity:** Implementing four specialized attention mechanisms (spatial, spectral, graph, and cross-modal) simultaneously in B-GFAN posed significant architectural challenges. Coordinating these attention types to work synergistically while maintaining computational efficiency required extensive experimentation and careful hyperparameter tuning to prevent attention conflicts and ensure stable convergence.
- **Uncertainty quantification calibration:** Achieving well-calibrated uncertainty estimates ($ECE = 3.1\%$) in B-GFAN required sophisticated mathematical frameworks combining aleatoric and epistemic uncertainty sources. The challenge involved propagating uncertainty through complex multi-modal attention layers while maintaining computational tractability for real-time clinical deployment.
- **Graph construction and validation:** Developing robust graph representations of EEG electrode connectivity with position uncertainty modeling proved challenging. Ensuring that the graph attention mechanisms learned clinically meaningful connectivity patterns rather than spurious correlations required extensive validation and domain expertise integration.
- **Generalization across diverse EEG data:** Achieving robust performance across varied and noisy real-world EEG data, which differs significantly from controlled or preprocessed training datasets, posed a major challenge for both frameworks. Ensuring the models maintain reliable seizure detection in diverse patient conditions required advanced feature extraction and comprehensive validation strategies.

8.2 Future Works

Although both proposed approaches achieved competitive results, there remain several opportunities for future improvement:

8.2.1 Dataset expansion and multi-center validation

While the CHB-MIT dataset provided comprehensive validation for both frameworks, future work should evaluate the methodologies on larger, more diverse multi-center datasets. For the B-GFAN framework, this includes assessing attention mechanism generalization across different clinical settings, while for ConvNeXt-BiLSTM, it involves testing scalogram-based feature extraction robustness. Incorporating datasets such as the

Temple University Seizure Corpus (TUSZ) and international EEG databases will help validate both frameworks' consistency across varied patient demographics, electrode configurations, and clinical protocols.

8.2.2 Lightweight model optimization and advanced architectures

Future research should explore lightweight variants of both frameworks to reduce computational demands. For ConvNeXt-BiLSTM, this involves investigating more efficient architectures like MobileNet, EfficientNet, and exploring advanced attention mechanisms like Efficient Channel Attention (ECA). For B-GFAN, future work should focus on transformer-based multi-modal attention, dynamic graph neural networks, and attention pruning techniques specifically designed for graph-based architectures to enable deployment on resource-constrained medical devices.

8.2.3 Enhanced uncertainty quantification and clinical decision support

Building upon the B-GFAN's Bayesian framework, future work should develop more granular uncertainty decomposition methods that separate attention-based uncertainty from model parameter uncertainty. This could enable more precise clinical risk stratification and adaptive monitoring protocols. For ConvNeXt-BiLSTM, incorporating uncertainty quantification mechanisms could enhance clinical reliability. Integration with existing clinical decision support systems and electronic health records could provide comprehensive uncertainty-aware seizure monitoring workflows for both approaches.

8.2.4 Addressing class imbalance and data augmentation

Future research should focus on developing more effective data balancing techniques tailored for real-world imbalanced EEG datasets. Advanced approaches such as GAN-based synthetic seizure generation, attention-guided oversampling for B-GFAN, and scalogram-specific augmentation techniques for ConvNeXt-BiLSTM could help mitigate class imbalance issues while preserving the clinical relevance of generated data.

8.2.5 Real-time optimization and federated learning

While both frameworks demonstrate real-time capabilities (4.64ms for ConvNeXt-BiLSTM, 12.3ms for B-GFAN), future research should focus on optimizing for edge deployment. Investigating federated learning approaches for graph attention in B-GFAN could enable privacy-preserving multi-center training, while developing efficient scalogram computation for ConvNeXt-BiLSTM could support wearable EEG systems.

8.2.6 Responsible AI and clinical interpretability

As both attention-based and uncertainty-aware seizure detection systems become more sophisticated, ensuring clinical interpretability and responsible deployment is crucial. Future research should develop standardized visualization techniques for attention patterns (multi-modal for B-GFAN, temporal for ConvNeXt-BiLSTM) that clinicians can readily interpret. Establishing clinical validation protocols for both frameworks' explanations and developing guidelines for responsible AI deployment will be essential for regulatory approval and clinical adoption while maintaining patient safety and trust.

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