PSG College of Technology

19I603 – Artificial Intelligence

KNOWLEDGE AND SERVICE

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Team - 9 Physics-informed attention temporal convolutional network for EEG-based motor imagery classification

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Dataset description:

Dataset Used : SEED_VIG_processed.csv

1.EEG Channels: The dataset consists of 17 unique EEG channels, each recording brain activity signals.
2.Timepoints: Every channel logs data at 384 distinct timepoints, indexed sequentially.
3.Subjects: EEG data was recorded from **12 individuals** while they were driving a simulator.
4.subindex: Represents the unique identifier for each subject.
5.substate: Indicates the **drowsiness status** of the subject:

- **0:** Normal (Awake)
- **1:** Drowsy (Fatigued)

6.EEG Feature Structure:
The EEG readings are arranged systematically, following this naming convention:
'EEG_Ch1_T1', 'EEG_Ch1_T2', ..., 'EEG_Ch1_T384'
This pattern continues for all 17 channels up to:'EEG_Ch17_T1', 'EEG_Ch17_T2', ..., 'EEG_Ch17_T384'
7.Total Columns in the Dataset:
The dataset comprises 6,530 columns in total, including EEG data and the two extra identifiers.
The breakdown is:

17 channels × 384 timepoints = 6,528 EEG features
+2 additional columns (subindex & substate)

Final count: 6,530 columns

Tabulation of Proposed Models and their results:

S.No	Model	Accuracy	Precision	Recall	F1-Score	TPR	TNR	FPR	FNR
01	EEG-ATCNet	0.942	0.95	0.94	0.94	0.89	0.99	0.01	0.11
02	Multiscale CNN, EEG-ATCNet, CBAM	0.9705	0.97	0.97	0.97	0.96	0.98	0.02	0.04
03	Multiscale CNN, EEG-ATCNet, CBAM,K Fold	0.9628	0.96	0.96	0.96	0.95	0.97	0.03	0.05
04	Multiscale CNN, EEG-ATCNet, CBAM,ICNN	0.9661	0.97	0.97	0.97	0.96	0.97	0.03	0.04
05	Multiscale CNN, EEG-ATCNet, SE-Attention mechanism	0.96499	0.97	0.96	0.96	0.95	0.98	0.02	0.05

Model 1: EEG-ATCNet

Proposed Methodology:

1.Continuous Wavelet Transformation (CWT): The raw EEG signals are transformed using a CWT with 30 scales and a Morlet wavelet to generate a detailed time-frequency representation.

2.Gaussian Noise Injection: A GaussianNoise layer is applied at the beginning to add controlled random noise, enhancing model robustness and reducing overfitting.

3.Initial Convolutional Feature Extraction: A convolutional block with 64 filters, combined with batch normalization, spatial dropout, and max pooling, extracts low-level features from the transformed data.

4.Adaptive Feature Fusion: Features from parallel convolution branches with 3×3 and 5×5 kernels are concatenated, fused with a 1×1 convolution, and integrated via residual connections for enhanced representation.

5.Deep Feature Refinement and Classification: Further processing with a 128-filter convolutional block, followed by global average pooling, a dense layer with dropout, and a final sigmoid-activated output layer, leads to binary classification.

Inference:

1.Strong Overall Performance: The model achieves high accuracy with a training accuracy of about 96% and a test/validation accuracy of around 94%, indicating effective learning and generalization.

2.Balanced Class Performance: Both classes have an F1-score of 0.94, demonstrating that the model performs robustly across different classes despite minor precision-recall trade-offs.

3.Class-Specific Insights: The confusion matrix reveals that most misclassifications involve class 1 being predicted as class 0 (48 instances), suggesting that while the model is very precise for class 1, it misses some actual class 1 samples.

4.Minimal Overfitting: The small gap between training and validation accuracies implies that the model is not significantly overfitting, maintaining solid performance on unseen data.

Model 2: Multiscale CNN,EEG-ATCNet,CBAM

Proposed Methodology:

1.Adaptive Feature Fusion: The `adaptive_feature_fusion_module_2d` function fuses features from parallel 3×3 and 5×5 convolution branches using concatenation, a 1×1 convolution, and a residual connection.

2.CWT: The `apply_cwt` function transforms EEG signals into time-frequency representations by applying a Continuous Wavelet Transform with 30 scales using a Morlet wavelet.

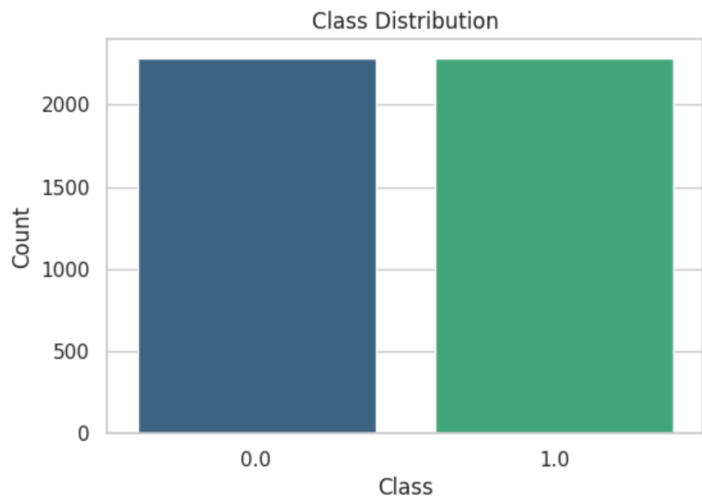
3.CBAM Attention: The `cbam_block` function implements the Convolutional Block Attention Module by combining channel and spatial attention mechanisms to enhance feature maps.

4.Multiscale CNN: The `attention_guided_multiscale_cnn_module` function builds a multiscale CNN by processing inputs through convolution branches with kernel sizes of 3×3, 5×5, and 7×7, then merging them with attention and residual connections.

5.Data Standardization: The `standardize_raw_data` function normalizes each EEG channel using StandardScaler, ensuring consistent scaling across samples for improved model training.

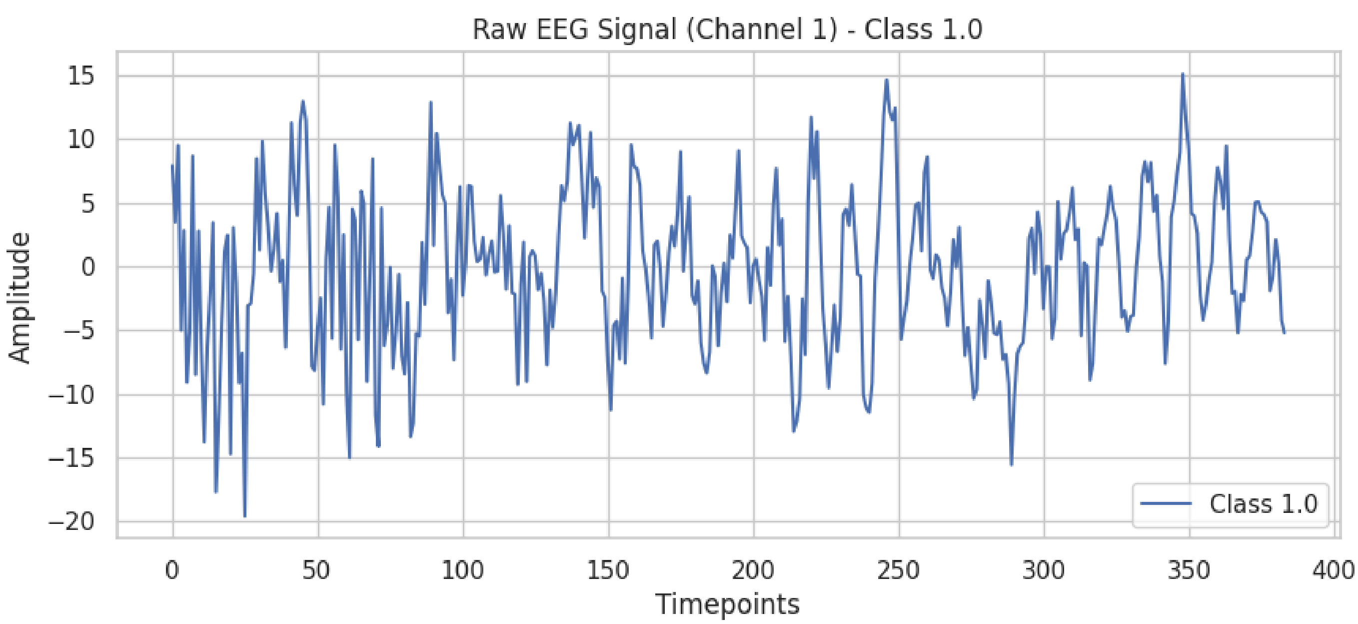
Inference:

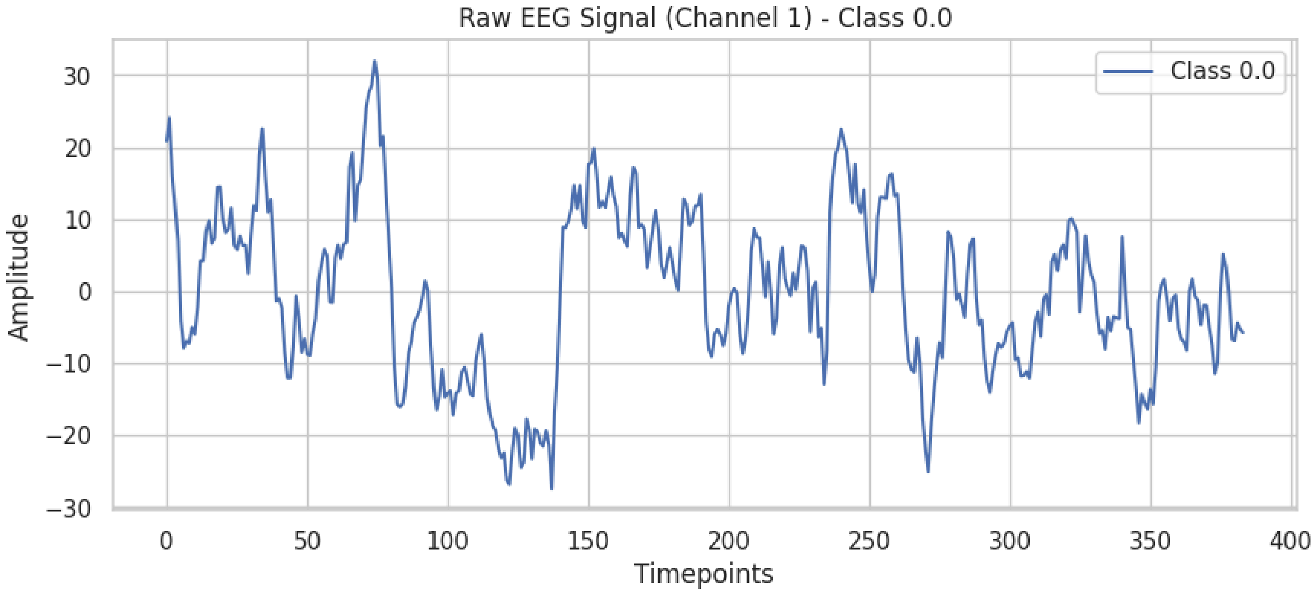
Checking for class imbalance



It shows that the two classes (0.0 and 1.0) have almost comparable counts, indicating a fairly balanced dataset with no severe class imbalance issue.

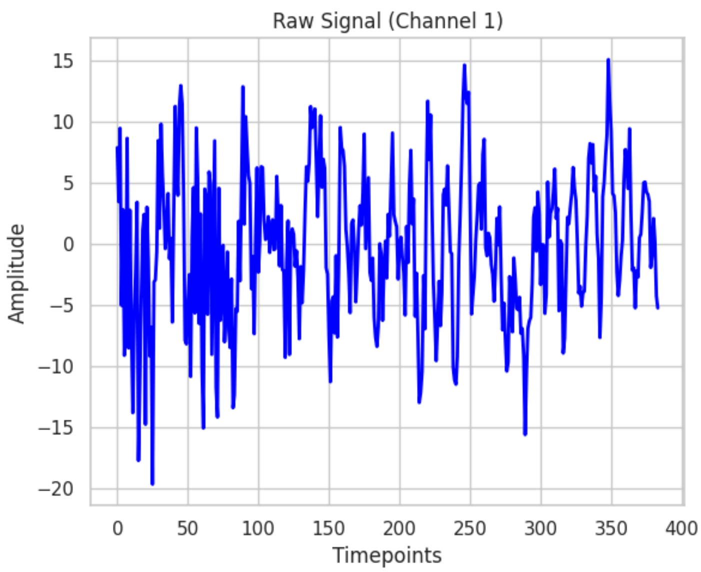
Raw EEG(channel 1) signals of a alert and drowsy person

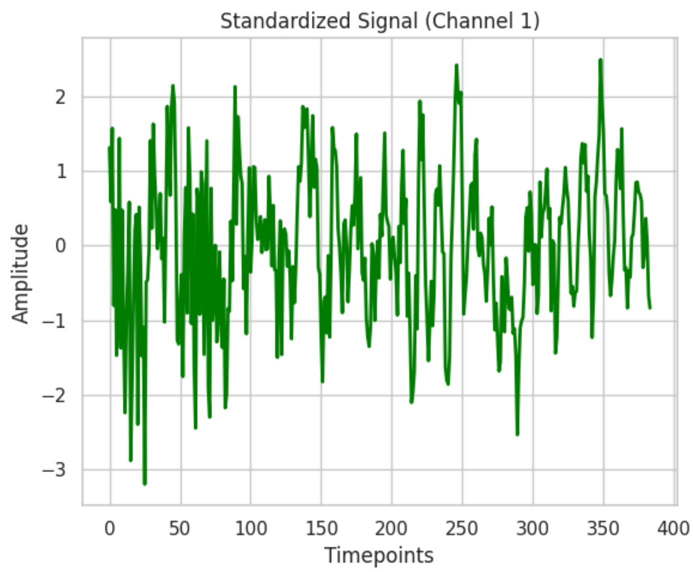




Both plots illustrate that the EEG signals vary in how much and how often their amplitudes rise and fall over time. Class 0.0 appears to have somewhat larger amplitude swings, while Class 1.0's signal shows slightly smaller or more frequent fluctuations—indicating there might be characteristic patterns distinguishing these two classes.

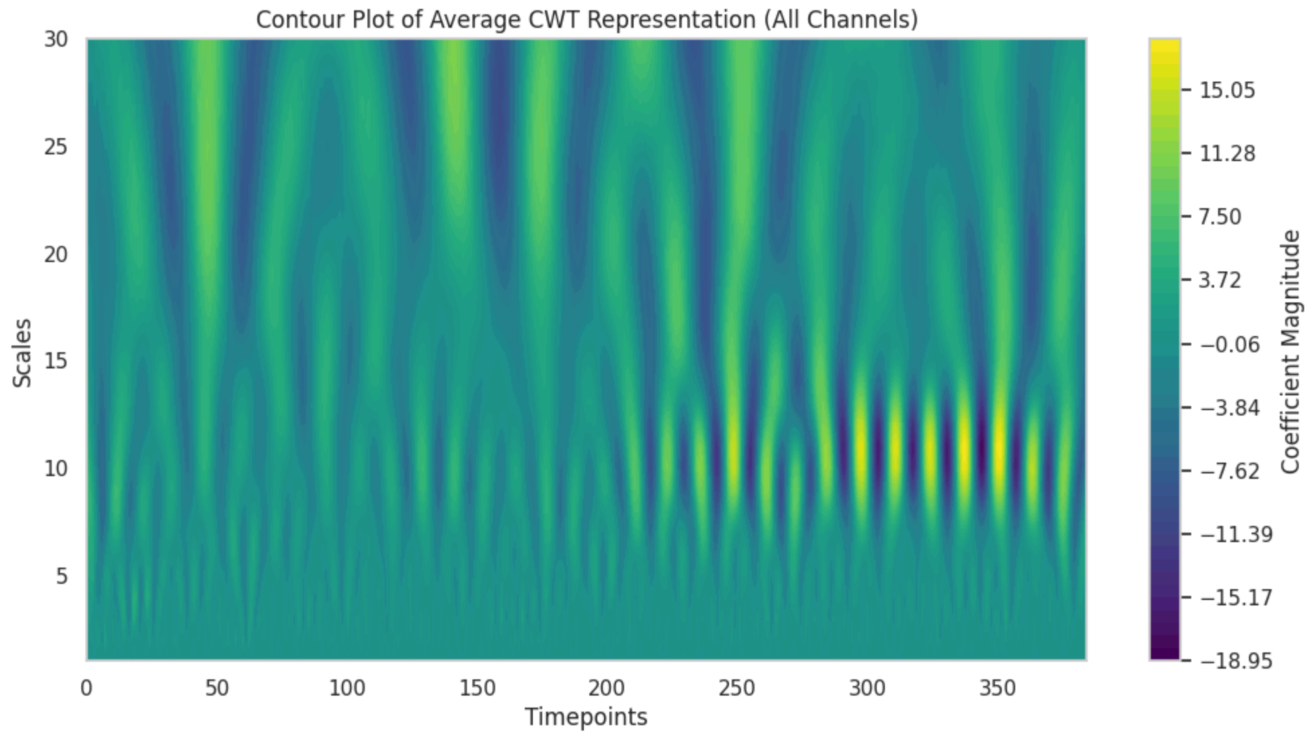
Raw vs Standardised EEG signals





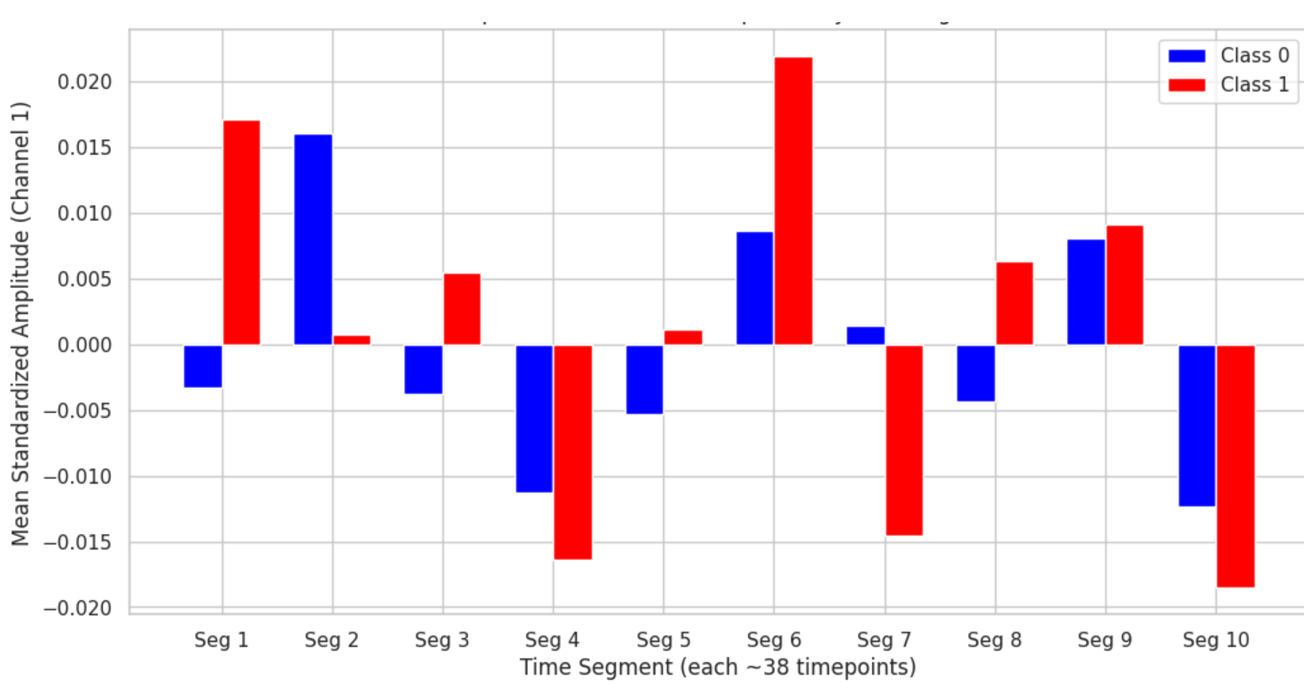
Both plots look nearly identical, indicating that the raw signal was already on a similar scale, so standardization didn't change the shape or amplitude range much—suggesting the data was effectively standardized beforehand.

Contour Plot of average CWT Representation



This contour plot illustrates how EEG signal energy (coefficient magnitude) is distributed across different frequencies (scales) over time. Areas with warmer colors represent higher energy at specific time-frequency regions. By examining these patterns, it becomes possible to identify which frequency ranges are most active at various time intervals, aiding in tasks like feature extraction or state classification (e.g., drowsiness detection).

Grouped Bar Chart:Mean Amplitude by Time Segment



This grouped bar chart compares the mean EEG amplitudes (after standardization) in discrete time segments for two classes (0 and 1). By visualizing data in this segmented manner, it becomes easier to spot which specific segments exhibit notable differences between the classes—potentially indicating where discriminative features may lie for tasks like classification or pattern analysis.

Model Evaluation Results:

1.High Overall Accuracy: The model achieves around 97% accuracy on both training and validation sets, indicating strong generalization to unseen data.

2.Balanced Class Performance:Precision, recall, and F1-scores are all around 0.97 for both classes, showing that the model handles both classes equally well.

3.Confusion Matrix Insights: Most misclassifications involve a small number of samples (10 false positives for class 0, 17 false negatives for class 1), reflecting only minor errors.

4.Minimal Overfitting: The close alignment between training (about 98%) and validation (about 97%) accuracy suggests the model is not significantly overfitting.

Model 3: Multiscale CNN,EEG-ATCNet,CBAM,K Fold

Proposed Methodology:

1.Data Preparation & Standardization: The raw EEG signals are reshaped, shuffled, and standardized (channel by channel) before each training fold to ensure consistent input scaling and enhance model training stability.

2.Time-Frequency Transformation:A Continuous Wavelet Transform (CWT) with multiple scales (1–30) and a Morlet wavelet is applied to the EEG data, producing rich time-frequency representations for each sample.

3.Multiscale CNN & Fusion Modules: The model architecture integrates modules such as temporal frequency attention, adaptive feature fusion, and an attention-guided multiscale CNN to extract diverse and robust features at different scales.

4.CBAM Attention Mechanism: Within the final convolutional flow, the Convolutional Block Attention Module (CBAM) is employed to refine feature maps by applying both channel and spatial attention, highlighting critical information while suppressing less relevant details.

5.K-Fold Cross Validation:A Stratified K-Fold approach systematically splits the dataset into training and validation folds, training the model multiple times to gauge its average performance and reduce variance in the results.

Inference:

1.High Overall Performance: The model consistently achieves an average accuracy of 96.17%, indicating strong predictive capability.

2.Low Variability: The small standard deviation of 0.54% across folds shows the model performs reliably across different splits.

3.Low Loss Value: An average loss of 0.2002 suggests that the model's predictions are close to the actual values.

4.Robust Generalization: These metrics together indicate that the model generalizes well and is robust to variations in the data.

Model 4: Multiscale CNN,EEG-ATCNet,CBAM,ICNN

1.CWT Transformation: The model uses a Continuous Wavelet Transform (CWT) to convert raw EEG signals into time-frequency representations, capturing both temporal and frequency information essential for effective feature extraction.

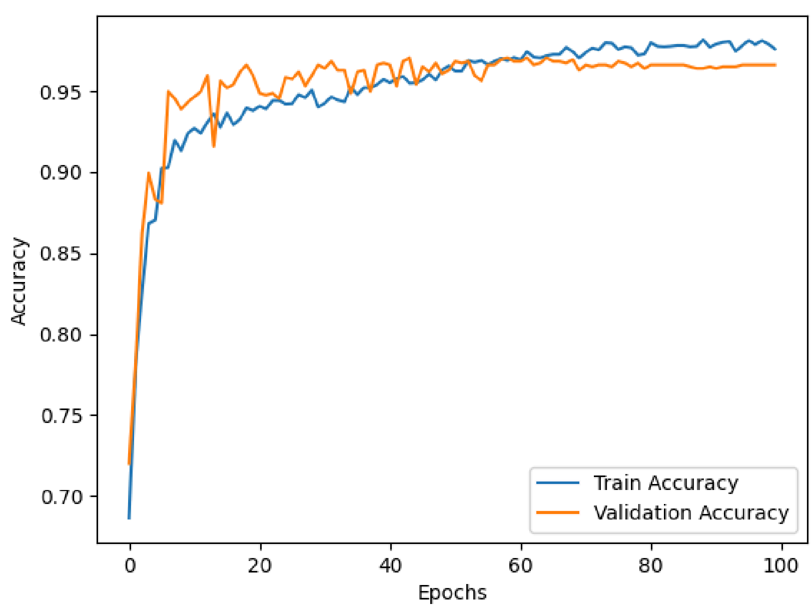
2.Multiscale CNN Module:A multiscale CNN module processes the CWT features with different kernel sizes (3×3, 5×5, and 7×7), enabling the network to capture patterns at various scales and improve the robustness of feature extraction.

3.CBAM Attention Mechanism: The CBAM block refines the feature maps by applying both channel and spatial attention—this helps the model emphasize the most relevant features and suppress irrelevant ones, leading to more discriminative representations.

4.ICNN Block: An ICNN block (implemented as a dense layer with non-negativity constraints) further refines the features after global average pooling, offering an additional non-linear transformation that enhances the final feature representation.
5.Overall Model Inference: By combining CWT-based time-frequency representation, multiscale CNN modules, CBAM attention, and ICNN feature refinement, the model effectively captures and processes complex EEG patterns, which is reflected in its strong performance during training and evaluation.

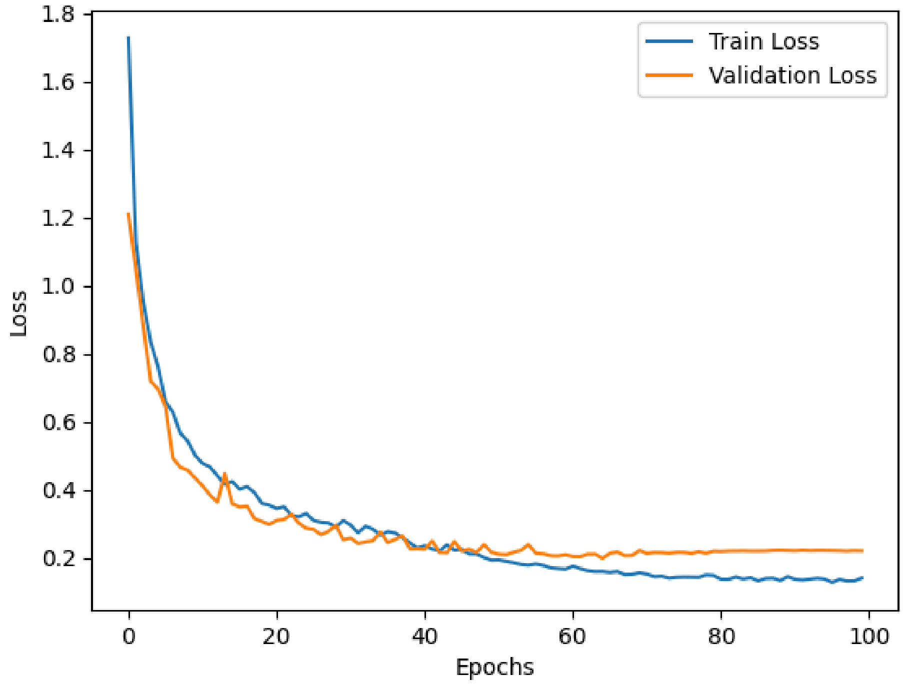
Inference:

Accuray Curve



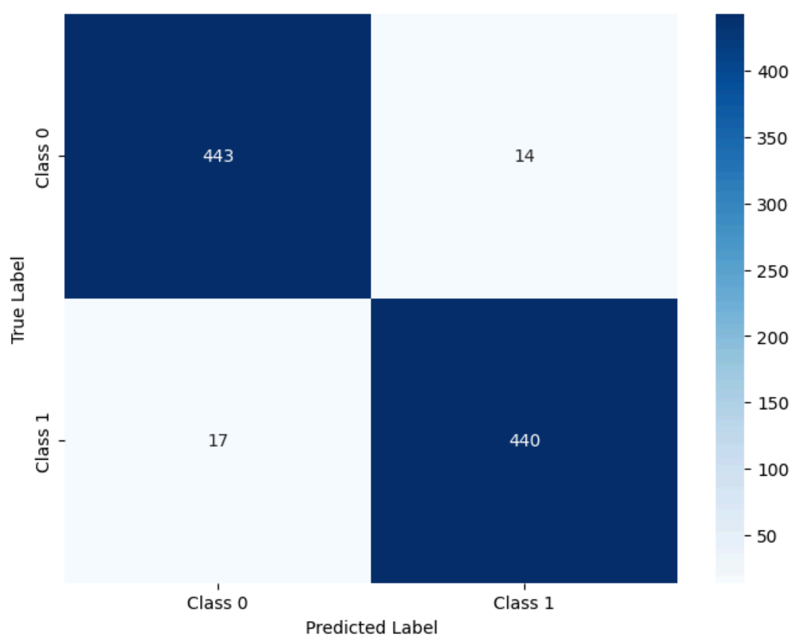
The training and validation accuracies both increase rapidly in the early epochs and remain close throughout, suggesting effective learning and minimal overfitting. By the later epochs, they stabilize at around 96%, indicating a robust generalization to unseen data.

Loss Curve



Both the training and validation loss curves steadily decrease, reflecting effective learning and convergence. The fact that they stay relatively close to each other suggests the model generalizes well without significant overfitting.

Confusion Matrix



The confusion matrix shows a well-performing model with high accuracy, as most predictions are correct: 443 True Negatives (Class 0) and 440 True Positives (Class 1), with low misclassification rates (14 False Positives, 17 False Negatives).

Model Evaluation Results:

1.High Accuracy: The model achieves a 96.6% accuracy, indicating strong performance in classifying drowsy and normal states.

2.Balanced Performance: Both classes (0 and 1) have high precision (0.96, 0.97) and recall (0.97, 0.96), showing no significant bias.

3.Low Test Loss: A low test loss (0.2198) suggests that the model generalizes well without major overfitting.

4.Strong F1-Score: The F1-score of 0.97 confirms a good balance between precision and recall, ensuring reliable classification.

Model 5: Multiscale CNN,EEG-ATCNet,SE-Attention mechanism

Proposed Methodology:

Multiscale CNN Feature Extraction:Utilizes multiple convolutional kernels (e.g., 3×3, 5×5, 7×7) within a single module to capture features at various spatial resolutions, allowing the network to learn both fine and coarse patterns from the EEG data.

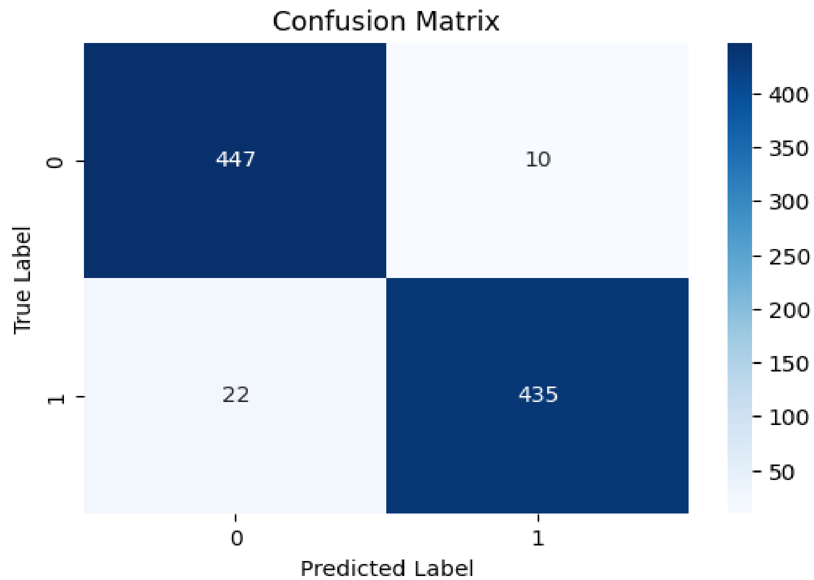
Enhanced Feature Fusion in Multiscale CNN: By concatenating outputs from different kernel sizes and subsequently fusing them, the network can integrate diverse feature representations, which is crucial for modeling the complex temporal and spatial dynamics inherent in EEG signals.

EEG-ATCNet Architecture: This model is tailored for EEG analysis and combines multiscale feature extraction with attention mechanisms to emphasize the most informative parts of the signal. It leverages time–frequency representations (e.g., via Continuous Wavelet Transform) to better capture transient brain activities.

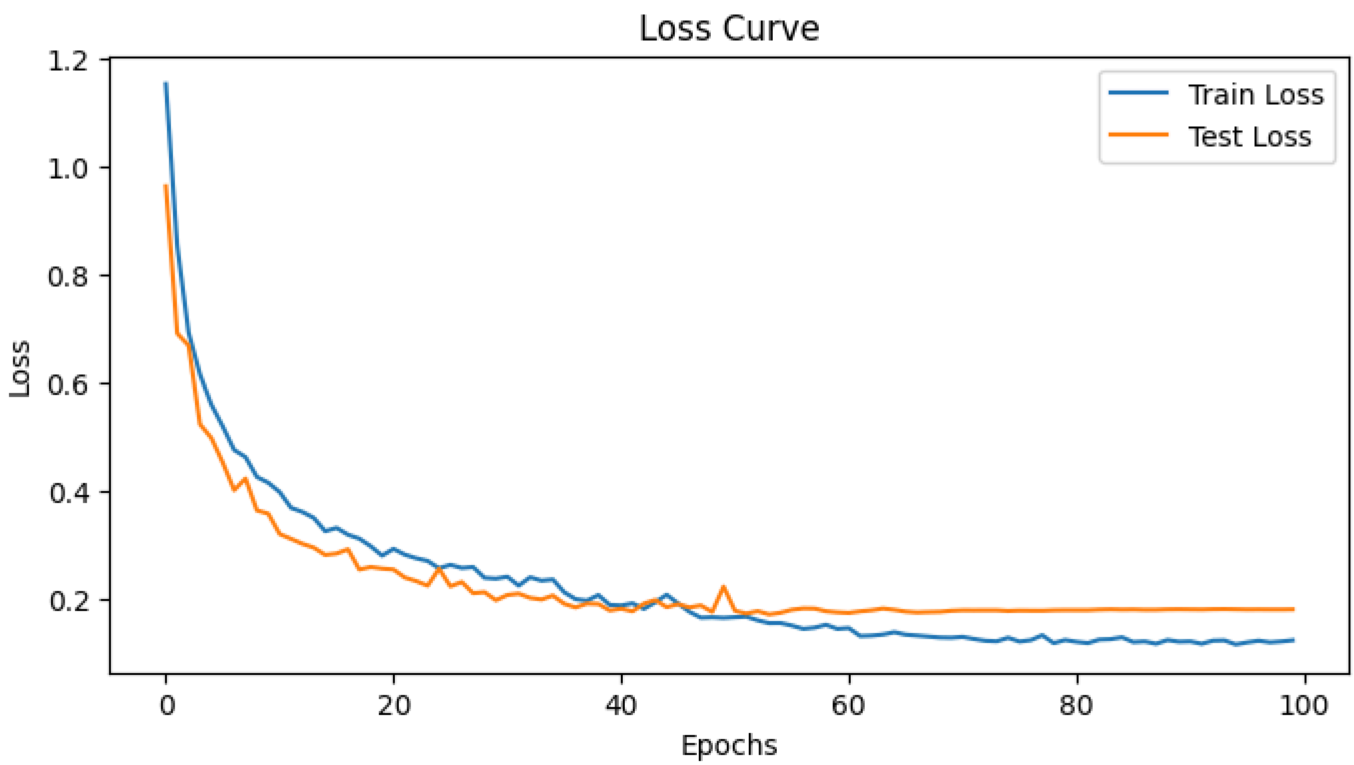
Focus on Relevant Signal Components: Within EEG-ATCNet, attention mechanisms guide the network to focus on critical time-frequency regions, enhancing its ability to discriminate between different states (like drowsy versus normal), thus improving classification performance.

SE-Attention Mechanism (Squeeze-and-Excitation): This module recalibrates channel-wise feature responses by using global pooling and a two-layer fully connected network to generate adaptive weights. These weights emphasize more informative channels while suppressing less relevant ones, further boosting the network's discriminative power.

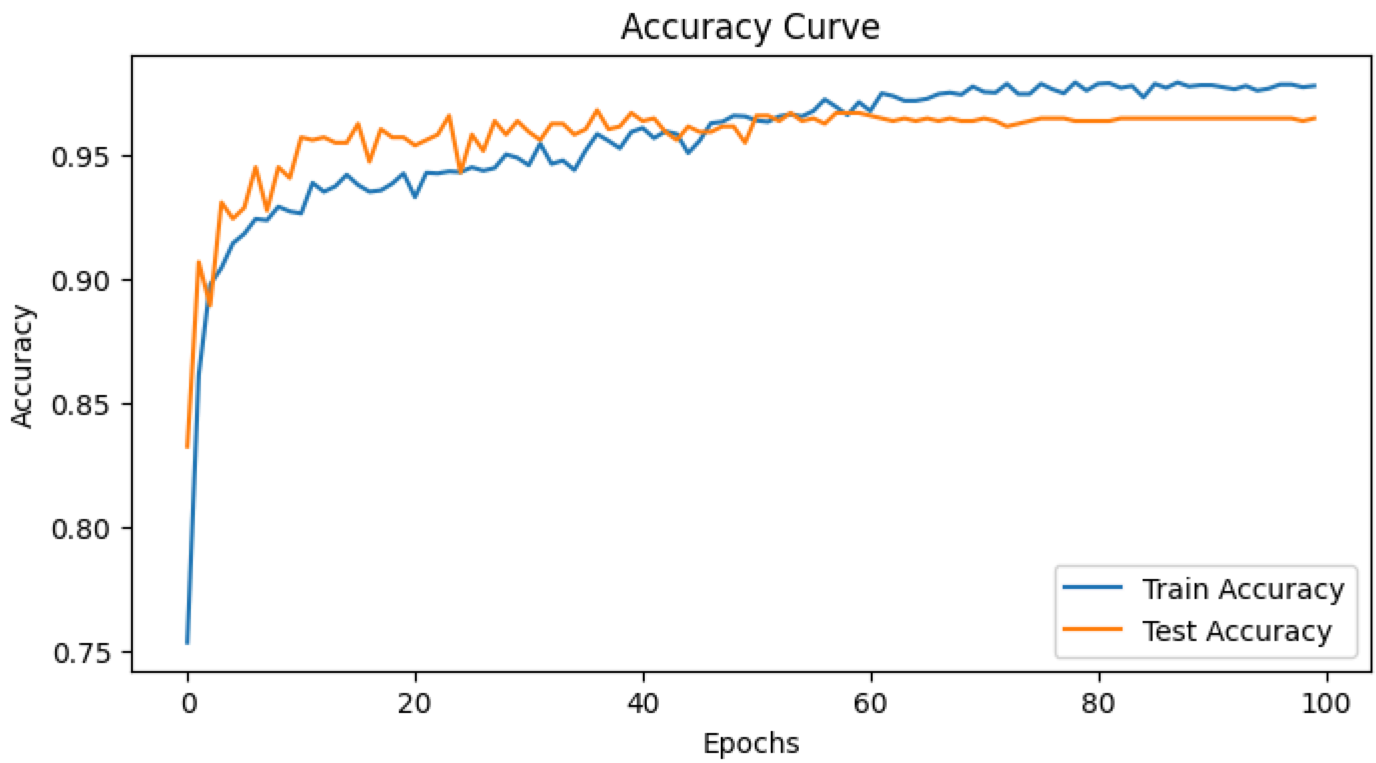
Inference:



This confusion matrix indicates strong performance, with 447 correct predictions for Class 0 and 435 correct predictions for Class 1. Only 10 false positives and 22 false negatives suggest the model effectively distinguishes between the two classes.



The Train Loss steadily declines, indicating effective learning and convergence over epochs. Meanwhile, the Test Loss follows a similar downward trend with a small gap, suggesting minimal overfitting and good generalization.



Both training and test accuracies improve steadily, indicating the model learns effectively over time. The small gap between them suggests minimal overfitting and strong generalization to unseen data.

Model Evaluation results:

High Accuracy: The model achieves nearly 97.8% on training and 96.5% on testing, indicating strong overall performance.

Balanced Performance: Both classes show high precision (0.95 and 0.98) and high recall (0.98 and 0.95), suggesting minimal bias.

Low Misclassification: The confusion matrix reveals only 10 false positives and 22 false negatives, reflecting robust classification capabilities.

Good Generalization: The small gap between training and test accuracy points to minimal overfitting, confirming the model generalizes well.

Futuristic recommendation and implementation:

- **Wearable Integration:** Embed the model in a wearable EEG device to monitor brain activity in real time, providing immediate drowsiness alerts.

- **Local Fine-Tuning:** Adjust a pre-trained model directly on each device using the user's own data, ensuring the model adapts to individual patterns while keeping data private.

- **Cloud-Based Model Updates:** Regularly update the model in the cloud with anonymized data from multiple devices, enhancing overall accuracy through broader learning.

- **Multimodal Data Fusion:** Combine EEG data with inputs from other sensors (like eye tracking) to improve the system's ability to detect drowsiness reliably.

- **User Feedback Loop:** Incorporate user feedback on alert accuracy to continually refine and enhance the model's performance over time**.**