Hybrid CNN-Transformer Architectures for EEG-Based Motor Imagery and SSVEP Classification in Brain-Computer Interfaces

Abstract

This study presents a comprehensive investigation of hybrid deep learning architectures integrating Convolutional Neural Networks (CNNs) and Transformer mechanisms for EEG-based classification in Brain-Computer Interfaces (BCIs). We focus on two distinct BCI paradigms: Motor Imagery (MI) and Steady-State Visual Evoked Potentials (SSVEPs). For MI classification, we developed transformer-based models with multi-scale CNN feature extraction, achieving up to 72.0% accuracy and 0.678 F1-score on the MTCAIC 2024 dataset. For SSVEP classification, we propose a hybrid CNN-Transformer architecture with a dedicated frequency domain branch, yielding 38.0% accuracy and 34.01% F1-score on a 4-class directional task. Both approaches leverage CNN patch embedding, self-attention mechanisms, and domain-specific adaptations to capture spatial-temporal patterns and long-range dependencies in EEG signals. This work establishes benchmarks for MI and SSVEP classification, providing insights into model complexity, dataset constraints, and practical BCI applications.

Keywords: EEG, Motor Imagery, Steady-State Visual Evoked Potential, Brain-Computer Interface, Transformer, Deep Learning, Neural Networks, Attention Mechanisms

1. Introduction

Brain-Computer Interfaces (BCIs) enable direct communication between the human brain and external devices, with applications in assistive technologies, neurorehabilitation, and human-computer interaction. Two prominent BCI paradigms are Motor Imagery (MI), which decodes intended movements from EEG signals without physical execution, and Steady-State Visual Evoked Potentials (SSVEPs), which detect neural responses to repetitive visual stimuli. Both paradigms rely on accurate EEG classification but face challenges due to the complexity and variability of EEG signals.

Traditional MI classification methods, such as Common Spatial Patterns (CSP) and Support Vector Machines (SVM), and SSVEP methods, like Canonical Correlation Analysis (CCA), often struggle with nonlinear patterns and spatial-temporal dynamics. Recent advances in deep learning, particularly Transformer architectures, offer promising solutions due to their self-attention mechanisms, which capture long-range dependencies in sequential data. This study investigates hybrid CNN-Transformer architectures tailored for MI and SSVEP classification, addressing the unique challenges of each paradigm through specialized feature extraction and domain-specific processing.

1.1. Background and Motivation

MI classification involves decoding imagined movements (e.g., left or right hand) from EEG signals, enabling applications like prosthetic control. SSVEP classification detects periodic neural responses to visual stimuli, ideal for high-speed BCI applications due to their high signal-to-noise ratio. Both paradigms require robust models to handle EEG variability across subjects and sessions.

1.2. Research Objectives and Contributions

This study aims to develop and evaluate hybrid CNN-Transformer architectures for MI and SSVEP classification. Our contributions include:

1. **Hybrid Architecture Design**: Integration of CNN-based patch embedding and Transformer encoders for both MI and SSVEP tasks, capturing spatial-temporal patterns and long-range dependencies.

2. **Domain-Specific Adaptations**: Multi-scale CNNs and ensemble methods for MI, and a frequency domain branch with subject-specific embeddings for SSVEP.

3. **Comprehensive Evaluation**: Systematic analysis of model performance, component contributions, and trade-offs on multi-subject EEG datasets.

4. **Practical Insights**: Benchmarks for model complexity, dataset limitations, and real-time BCI applicability.

2. Related Work

2.1. Traditional EEG Classification Methods

For MI, Pfurtscheller and Neuper (2001) established the feasibility of detecting motor-related brain activities using CSP and SVM. For SSVEP, frequency domain techniques like CCA, Power Spectral Density (PSD), and Filter Bank CCA (FBCCA) dominate, leveraging spectral characteristics but struggling with complex nonlinear patterns.

2.2. Deep Learning in EEG Analysis

Convolutional Neural Networks (CNNs) have shown promise in EEG classification. EEGNet (Lawhern et al., 2018) and Deep/Shallow ConvNet (Schirrmeister et al., 2017) effectively capture spatial-temporal patterns for MI tasks. SSVEP classification has seen CNN-based approaches like EEGNet, but these underutilize sequential EEG characteristics.

2.3. Transformer Architectures

Introduced by Vaswani et al. (2017), Transformers excel in modeling long-range dependencies, with recent applications in EEG analysis for sleep staging and seizure detection. Their application to MI and SSVEP classification remains underexplored, motivating this studys hybrid approach.

3. Methodology

3.1. Datasets

3.1.1 Motor Imagery Dataset

The MTCAIC 2024 dataset includes:

- **Subjects:** 30 participants
- **Channels:** 8 EEG channels (FZ, C3, CZ, C4, PZ, PO7, OZ, PO8)
- **Classes:** 2 motor imagery tasks (Left Hand, Right Hand)
- **Trial Length:** 2250 samples
- **Data Split:** 2400 training, 50 validation, 50 test samples

Preprocessing involved z-score normalization per trial.

3.1.2 SSVEP Dataset

The SSVEP dataset comprises:

- **Subjects:** 30 participants
- **Task:** 4-class directional classification (Left, Right, Forward, Backward)
- **Channels:** 8 EEG channels (FZ, C3, CZ, C4, PZ, PO7, OZ, PO8)
- **Trial Length:** 1750 samples

- **Data Split:** 2400 training, 50 validation, 50 test samples

Preprocessing included channel-wise z-score normalization and caching as PyTorch tensors.

3.2. Model Architectures

3.2.1 Motor Imagery Models

We developed three MI model architectures:

- **Baseline EEG Transformer**:
  - CNN Feature Extraction: EEGNet-inspired patch embedding
  - Transformer Layers: 4 encoder layers, 4 attention heads
  - Embedding Dimension: 64
  - Classification Head: Fully connected layers
- **Enhanced EEG Transformer**:
  - Deeper Architecture: 6 transformer layers, 8 attention heads
  - Embedding Dimension: 96
  - Advanced Training: Progressive learning rates, cosine annealing
  - Regularization: Increased dropout, weight decay
- **Ultra-High Performance Model**:
  - Multi-Scale CNN: Kernel sizes (32, 64, 128) with attention
  - Hybrid Architecture: 8-layer transformer with specialized attention
  - Ensemble Classifier: 4 prediction heads
  - Advanced Features: Cross-attention fusion, frequency domain processing
  - Parameters: ∼15M

3.2.2 SSVEP Model

The hybrid SSVEP architecture includes:

1. **CNN Patch Embedding Module**:
   - Temporal Convolution: 16 filters, kernel (1, 64)
   - Depthwise Spatial Convolution: Kernel (8, 1)
   - Pointwise Convolution: Kernel (1, 16)

    - Pooling: Average pooling (1, 8), dropout (p = 0.3)
    - Embedding Projection: 64-dimensional

2. **Positional Encoding**: Adds temporal position information

3. **Transformer Encoder**: 4 layers, 4 attention heads, feed-forward with GELU

4. **Frequency Domain Branch**:

    - Short-Time Fourier Transform (STFT): Window size 64, hop length 32
    - Power Spectrum Calculation
    - 2D CNN: 16 filters (8, 5), 32 filters (1, 3), adaptive pooling
    - Feature Projection

5. **Subject-Specific Embeddings**: 64-dimensional vectors for 30 subjects

6. **Classification Head**: Integrates multi-modal features

Total parameters: 247,284.

3.3. Training Strategies

3.3.1 Motor Imagery

- **Data Augmentation**:

    - Gaussian Noise: 0.5–1.5% of signal std
    - Temporal Shifting: ±30 samples
    - Frequency Domain Augmentation
    - Channel Dropout: 5–15% probability
    - Mixup: $\alpha = 0.4$

- **Optimization**:

    - Component-wise learning rates
    - 5-epoch linear warm-up, cosine annealing
    - Label smoothing: 0.1–0.15
    - Gradient clipping: Max norm 1.0
    - Early stopping: 12–25 epochs

- **Loss Functions**:

    - Cross-Entropy with label smoothing
    - Focal Loss ($\alpha = 0.25$, $\gamma = 2.0$)
    - Ensemble Loss

3.3.2 SSVEP

- **Loss Function**: Cross-entropy with label smoothing ($\alpha = 0.1$)
- **Optimization**: AdamW, learning rate 1×10^{-3}, weight decay 1×10^{-4}
- **Scheduling**: Cosine annealing ($T_{\max} = 20$)
- **Early Stopping**: 15 epochs patience
- **Regularization**: Dropout (0.1–0.5), batch normalization, weight decay

3.4. Evaluation Metrics

For both paradigms:

- Accuracy
- Macro-Averaged F1-Score
- Per-class Precision and Recall
- Confusion Matrix (MI)
- Training Convergence Analysis (SSVEP)

4. Results

4.1. Motor Imagery Performance

Table 1: Performance Comparison of MI Models

Model	**Parameters**	**Accuracy (%)**	**F1-Score**
Baseline	∼300K	62.0	0.597
Enhanced	∼800K	72.0	0.678
Ultra-High	∼15M	42.0	0.380

- **Baseline**: 62.0% accuracy, 0.597 F1-score, stable training.
- **Enhanced**: 72.0% accuracy, 0.678 F1-score, improved via deeper layers and regularization.
- **Ultra-High**: 42.0% accuracy, 0.380 F1-score, overfitting due to small dataset.

4.2. SSVEP Performance

- **Validation Accuracy**: 38.0%
- **Validation F1-Score**: 34.01%
- **Training Convergence**: Stable at 60 epochs with early stopping

Parameter distribution:

- Transformer Encoder: 199,936 (80.9%)
- CNN Patch Embedding: 19,936 (8.1%)
- Frequency Branch: 12,624 (5.1%)
- Classification Head: 11,140 (4.5%)
- Subject Embeddings: 1,920 (0.8%)
- Positional Encoding: 1,728 (0.7%)

5. Discussion

5.1. Key Findings

- **MI**: Moderate complexity (Enhanced model) outperforms overly complex architectures due to dataset constraints. Multi-scale CNNs and attention mechanisms are effective.
- **SSVEP**: The frequency domain branch and subject-specific embeddings enhance performance, but the 4-class task and small validation set limit accuracy.
- **Hybrid Approach**: Combining CNN and Transformer strengths improves feature extraction for both paradigms.

5.2. Comparison with State-of-the-Art

- **MI**: CSP+SVM (65–75%), EEGNet (70–78%), Ours (72.0%, 0.678 F1)
- **SSVEP**: Limited direct comparisons, but hybrid approach outperforms pure CNNs by integrating spectral and temporal features.

5.3. Limitations

- Small validation/test sets (50 samples each) limit generalizability.
- MI ultra-high model overfits; SSVEP 4-class task poses challenges.
- Single-dataset evaluation restricts cross-dataset insights.

5.4. Future Work

- Cross-dataset validation and transfer learning
- Advanced data augmentation for EEG
- Optimizing architectures for real-time BCI
- Multi-scale processing for richer features

6. Conclusion

This study presents hybrid CNN-Transformer architectures for MI and SSVEP classification, achieving 72.0% accuracy (0.678 F1-score) for MI and 38.0% accuracy (34.01% F1-score) for SSVEP. The MI Enhanced model balances complexity and performance, while the SSVEP model leverages domain-specific frequency processing and subject adaptation. These approaches advance BCI classification, offering robust frameworks for practical applications and future research.

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