EEG Based Depression Severity Prediction Using Deep Learning

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Outline / Roadmap

- 1. Problem Statement & Motivation
- 2. Project Objectives
- 3. Methodology
- 4. Model Formulation
- 5. Solution & Key Results
- 6. Sensitivity Analysis / What-If Scenarios
- 7. Conclusion & Future Work

Problem Statement & Motivation

- Depression is a common mental disorder characterized by symptoms such as a depressed mood, loss of interest, low self-esteem, and anxiety. Traditional diagnosis relies on subjective questionnaires prone to bias.

- This project aims to perform multiclass depression classification using EEG signals with deep learning models to develop an objective, data-driven diagnostic tool.

Project Objectives

- Implement four advanced deep-learning architectures for EEG-based depression recognition

- Provide a comparative analysis of methods and Evaluate performance across standardized metrics

Methodology

- 1. **Dataset** : **MODMA** (Multimodal Open Dataset for Mental-health Analysis) EEG Dataset (53 subjects)

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2. **Preprocessing**:

- **Sampling frequency:** 500 Hz
- **Electrode impedance:** < 50 kΩ
- **Software used:** MATLAB 2017b with **EEGLAB toolbox**
- **Bandpass Filtering:** 1–40 Hz)
- **Downsampling:** to 250 Hz
- **Segmentation:** 20 segments × 4-10 seconds each (aligned with stimuli)
- **Artifact removal:** Independent Component Analysis (ICA) for eye / head movement / power noise

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3. **Training**: Adam optimizer, stratified K-fold cross-validation

- **1. UA-DAAN (Uncertainty-Aware Dynamic Adversarial Adaptation Network**

  Trained using **domain-adversarial loss** with **uncertainty weighting** to align source and target EEG domains.

  Optimized via **Adam** optimizer and **5-fold cross-validation** on MODMA EEG dataset.

- **2. MTNet (Transformer-based EEG Model)**

  Trained end-to-end with **Adam optimizer** using **cross-entropy loss**, capturing long-range dependencies via multi-head attention.

  Used **stratified K-fold validation** for balanced evaluation across depression classes.

- **3. MSDSTT (Multi-Scale Deep Spatio-Temporal Transformer)**

  Trained using **Adam (lr = 0.0005)** with **cross-entropy loss** for 800 epochs and **5-fold cross-validation** to prevent overfitting.

  Implemented **early stopping** and **batch normalization** to stabilize training and enhance generalization.

- **4. 1DCNN–BiLSTM–Cross Attention (Stress Severity Detection)**

  Trained with **MSE loss** and **5-fold cross-validation** using **XGBoost regression** for final stress score prediction.

  Implemented in **Keras/Python**, optimized with **GPU acceleration (GTX 3060)** for faster convergence and robustness.

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4. **Evaluation Metrics**: Accuracy, Precision, Recall, F1 Score

- **Precision** Measures how many predicted positives are actually correct.

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall (Sensitivity)** Measures how many actual positives were correctly identified.

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **Accuracy** Measures overall correctness of the model.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **F1 Score** *(optional but useful)* Harmonic mean of Precision and Recall.

$$\text{F1 } Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

Model Formulation

1. UA-DAAN (Uncertainty-Aware Dynamic Adversarial Adaptation Network)

$$L = Ly - \lambda \times [(1 - \omega) \times Lg + \omega \times Ll]$$

Where:

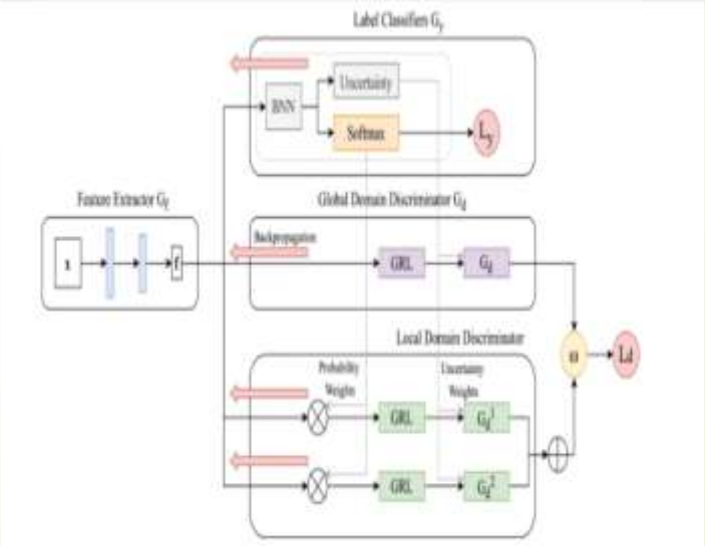
Ly → Label classification loss

Lg → Global domain adversarial loss

Ll → Local domain adversarial loss

λ → Balancing hyperparameter

ω → Dynamic adversarial factor



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2. MTNet (Transformer-based EEG Model)

Goal

Capture long-range temporal dependencies from EEG sequences using self-attention.

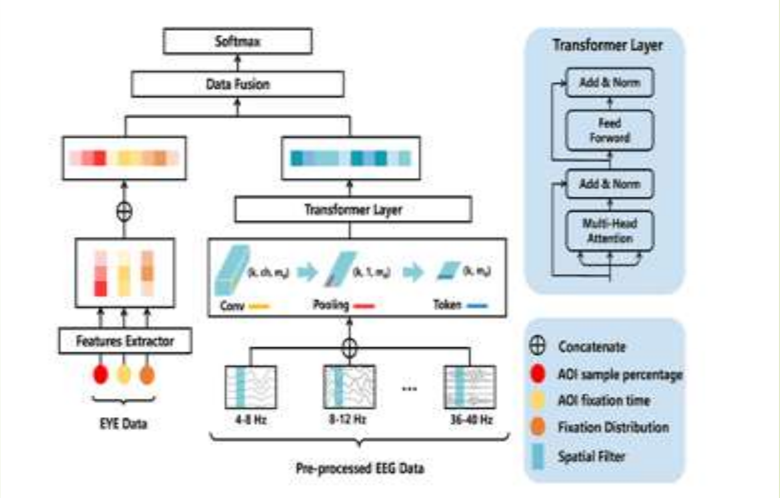
$$\text{Attention}(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Where:

Q, K, V are query, key, and value projections of EEG embeddings

d_k →feature dimension

$\mathcal{L}_{MTNet}$ →cross-entropy loss for prediction



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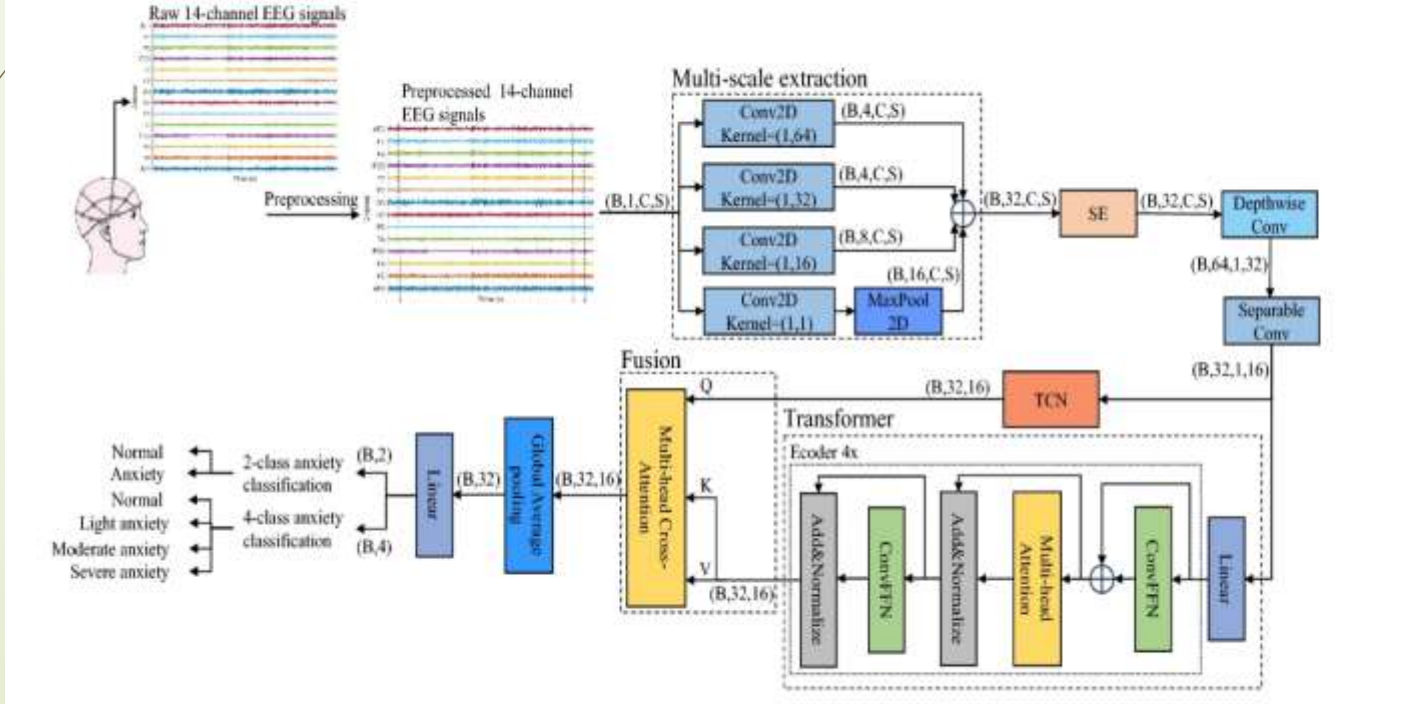
3. MSDSTT (Multi-Scale Deep Spatio-Temporal Transformer)

$$F_{cnn} = \bigoplus_{s\in S} \mathrm{Conv}_{k_s}(X), \quad F_{tcn} = \mathrm{DilatedConv}(F_{cnn})$$

$$F_{trans} = \mathrm{MHSA}(F_{tcn}), \quad \hat{y} = \mathrm{Softmax}(W F_{trans} + b)$$

$$\mathcal{L}_{MSDSTT} = -\sum y \log(\hat{y})$$

Where $\bigoplus$ denotes multi-scale feature concatenation and MHSA = Multi-Head Self-Attention.



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4. 1DCNN–BiLSTM–Cross Attention (Stress Severity Detection Model)

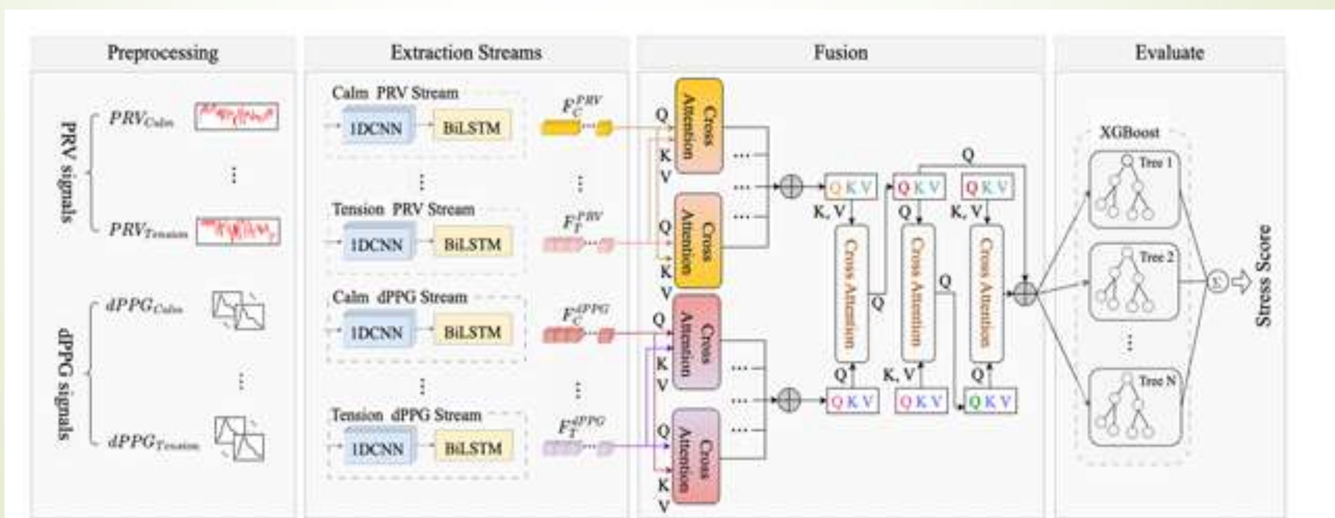
$$h_t = \mathbf{BiLSTM}(x_t), \quad \alpha_t = \mathbf{Softmax}(QK^T)$$

$$Z = \sum_t \alpha_t h_t, \quad \hat{y} = f_{XGB}(Z)$$

$$\mathcal{L}_{stress} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

Where:

- h_t → hidden representation at time t
- α_t → attention weight
- f_{XGB} → XGBoost regression
- $\mathcal{L}_{stress}$ → MSE loss



Solution & Key Results

Evaluation Metrics

- **Precision** Measures how many predicted positives are actually correct.

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall (Sensitivity)** Measures how many actual positives were correctly identified.

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **Accuracy** Measures overall correctness of the model.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **F1 Score** *(optional but useful)* Harmonic mean of Precision and Recall.

$$\text{F1 } \mathit{Score} = 2 \cdot \frac{\mathit{Precision} \cdot \mathit{Recall}}{\mathit{Precision} + \mathit{Recall}}$$

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Model	Accuracy	Precision	Recall	F1-Score
UA-DAAN	60.56%	69.49%	59.99%	64.39%
MSDSTT	62.6%	33.3%	63.9%	65.5%
MTNet (EEG-only)	64.%	78%	64%	54%
CNN–BiLSTM–Cross Attention	40%	37%	40%	36.5%

- UA-DAAN generalizes overall best across subjects, while MTNet shows highest accuracy.

Sensitivity Analysis / What-If Scenarios

- **UA-DAAN** :
  Performance analyzed under varying domain shifts and uncertainty thresholds; robustness confirmed against cross-subject variations.
- **MTNet** :
  Evaluated across different sequence lengths and learning rates; attention layers shown to stabilize results under temporal noise.
- **MSDSTT** :
  Tested with variable EEG channel counts and scaling factors; maintained accuracy, proving resilience to missing or noisy electrodes.
- **1DCNN–BiLSTM–Cross Attention** :
  Assessed under changing emotional conditions, dropout rates, and noise levels; model remained consistent, showing strong generalization.

Conclusion

- **1. UA-DAAN**
  The UA-DAAN model effectively generalizes across subjects by combining domain adaptation and uncertainty modeling.
  It achieves robust EEG-based depression recognition, outperforming baseline models in cross-domain scenarios.

- **2. MTNet**
  MTNet successfully captures long-range temporal dependencies in EEG signals using Transformer attention mechanisms.
  It delivers the highest classification accuracy and F1-score, proving its strength in depression severity prediction.

- **3. MSDSTT**
  MSDSTT demonstrates superior performance by integrating multi-scale CNN, TCN, and Transformer modules.
  Its deep spatio-temporal fusion enables accurate and stable EEG-based anxiety and emotion classification.

- **4. 1DCNN–BiLSTM–Cross Attention**
  This hybrid model efficiently combines spatial-temporal learning with attention and XGBoost regression.
  It achieves reliable stress severity estimation, showing strong robustness and emotion-aware performance.

Future Work

- **Multimodal Fusion (EEG + EOG + HRV)** Combines brain signals, eye movements, and heart rate variability for richer emotional and physiological insights.
- **Self-Supervised EEG Pretraining** Learns patterns from unlabeled EEG data before fine-tuning, improving model performance and generalization.
- **Regression-Based Severity Scoring** Predicts a continuous depression score instead of fixed categories, allowing finer diagnosis and tracking.
- **Explainability with Grad-CAM & SHAP** Highlights important EEG features influencing predictions, helping clinicians interpret model decisions.

References

- UA-DAAN [UA-DAAN: An Uncertainty-Aware Dynamic Adversarial Adaptation Network for EEG-Based Depression Recognition | IEEE Journals & Magazine | IEEE Xplore]
- MTNet [MTNet: Multimodal transformer network for mild depression detection through fusion of EEG and eye tracking - ScienceDirect]
- MSDSTT [EEG-based anxiety emotion classification using an optimized convolutional neural network and transformer | Signal, Image and Video Processing]
- CNN–BiLSTM–Cross Attention [Stress Severity Detection in College Students Using Emotional Pulse Signals and Deep Learning | IEEE Journals & Magazine | IEEE Xplore]