DSEA-Net: Multi-Dimensional Attention Fusion Framework for EEG-Based Depression Diagnosis

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***Abstract*—Major depressive disorder imposes a severe global health burden, highlighting the critical need for objective diagnostic tools. Electroencephalography (EEG) offers a promising avenue, but automated detection faces key challenges: susceptibility to noise and complex signal dynamics, bias from manual preprocessing engineering, and limited clinical applicability due to poor generalization and low interpretability. To address these limitations, we propose DSEA-Net, a lightweight multidimensional attention network for EEG-based depression diagnosis. DSEA-Net synergistically integrates Channel Attention, Neuro-Spectral Excitation Block (NeuroSE-Block), and Deep Attention mechanisms within an efficient architecture. The channel attention module dynamically weights electrode contributions to enhance spatial feature learning. The NeuroSE-Block explicitly incorporates neurophysiological priors of depression biomarkers for frequency-band-specific and channel-adaptive feature recalibration. The deep attention module refines feature representations across network layers. Extensive experiments on two real-world datasets under rigorous subject-independent protocols demonstrate DSEA-Net's superior performance: achieving state-of-the-art accuracies of 94.6% on MODMA and 97.33% on EDRA. Moreover, derived attention maps provide neurophysiologically plausible interpretations, aligning with established biomarkers like prefrontal alpha asymmetry. DSEA-Net presents a significant advancement towards clinically applicable, interpretable, and robust EEG-based depression detection.**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

Depression exerts a profound and multifaceted impact on global health, manifesting as both a debilitating mental disorder and a significant contributor to physical morbidity. Recent WHO data reveals the staggering global burden of depression [1].Clinical depression affects over 280 million people worldwide (3.8% of the population) and is linked to more than 700,000 suicide deaths annually. These figures highlight the urgent need for more effective detection methods given its high prevalence and limitations of current diagnostics.

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To address these limitations in diagnosis, objective biomarkers are crucial. EEG has emerged as a promising candidate for objective depression biomarkers, offering non-invasive measurement and high temporal resolution to capture the brain's dynamic activity [2]. While recent advances in deep learning enable automated EEG analysis, existing models face significant limitations hindering clinical diagnosis. First, EEG signals are inherently noisy (susceptible to ocular artifacts, muscle movements) and exhibit complex nonlinear dynamics [3]. Traditional denoising pipelines like independent component analysis (ICA) [4] and wavelet thresholding [5] often require manual tuning, introducing bias. Second, many deep learning approaches depend on handcrafted feature engineering (e.g., spectral power asymmetry, functional connectivity) [6], potentially overlooking subtle, depression-specific patterns within raw signals. Third, models trained on single datasets frequently suffer performance degradation on new populations due to inter-device variability and cohort heterogeneity [7].

To address these challenges, we propose DSEA-Net, a lightweight neural network for EEG-based depression detection. By integrating multiple attention mechanisms into a compact feature extraction framework, it effectively captures multi-dimensional features and improves classification performance. The main contributions are summarized as follows.

- **Designing a lightweight benchmark network** for depression EEG signal detection, which combines the main feature extraction architectures of ConvNet [8] and EEG-Net [9]. Separable convolution is employed to reduce the number of network parameters, thereby enhancing the model's generalization ability and training efficiency.

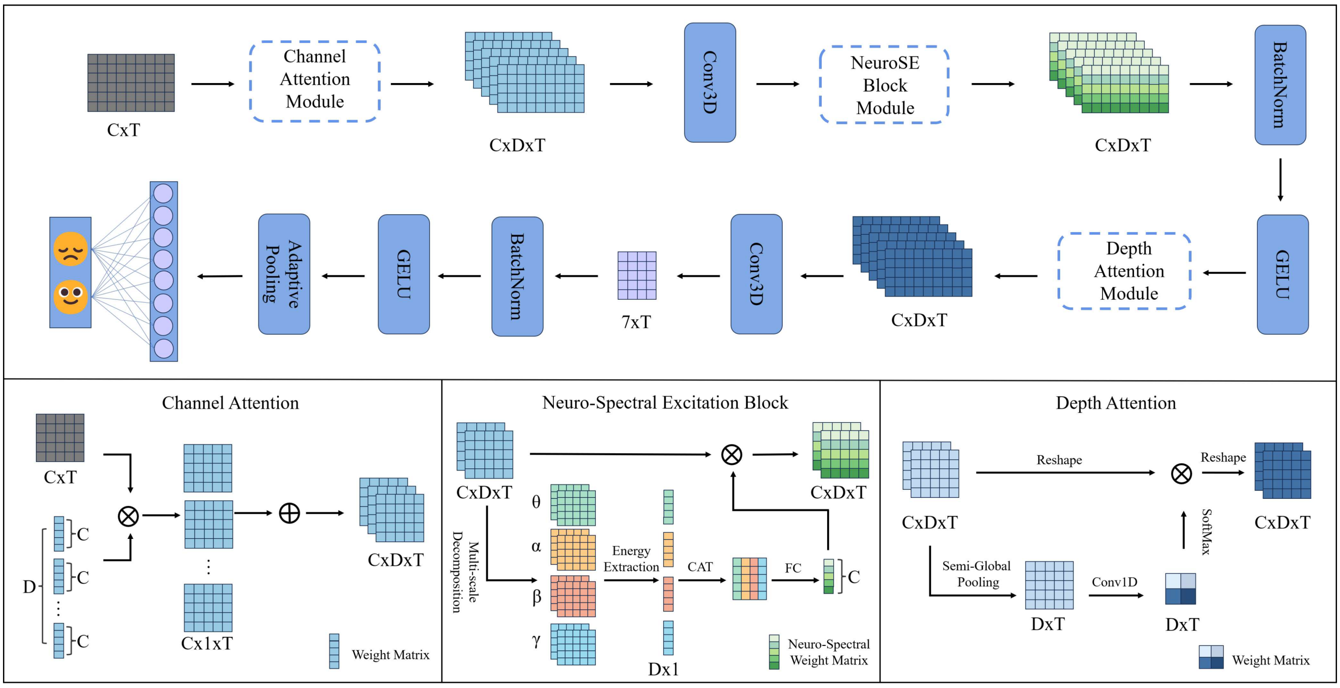

Fig. 1. The architecture of the DSEA-Net.where C is the number of EEG channels, T is the number of time samples in a trial. Other parameters are also shown in the figure.

Moreover, adaptive average pooling allows for dynamic adjustment of the number of parameters in accordance with varying EEG tasks and acquisition devices.

- **Fusing channel attention, neuro-spectral excitation block, and deep attention module**Enables effective extraction and integration of multi-dimensional features. The channel attention module enhances spatial features, while the deep attention module captures depth-related information. NeuroSE-Block adapts to individual-specific features, reducing variability in classification. Additionally, Class Activation Map (CAM) provides interpretable visualization by mapping features to temporal or spatial domains.
- **Conducting comprehensive experiments to prove the effectiveness of DSEA-Net** Experiments on two real-world EEG depression datasets used ten-fold cross-validation and multiple metrics to evaluate DSEA-Net against state-of-the-art models. Results show that DSEA-Net consistently outperforms existing methods, demonstrating strong performance and generalizability.

II. Related Work

Early work on EEG-based depression detection primarily relied on extracting spectral and temporal features through manual feature engineering, followed by standard machine learning classifiers [10]–[12]. For instance, Movahed et al. [13] extracted power and nonlinear features from multiple EEG bands, achieving around 90% accuracy using classifiers like KNN and LR. However, the performance of such approaches is inherently constrained by the quality and completeness of the manually designed features.

Deep learning has become the dominant approach, demonstrating significant power in learning discriminative representations directly from EEG data [14]. Li et al. [15] established a CNN framework for mild depression recognition, showcasing CNNs' ability to capture spatiotemporal patterns from raw EEG. Zhu et al. [16] employed FFT and EMD to transform EEG signals into multispectral images for CNN classification. To more explicitly model complex temporal dynamics alongside spatial features, Song et al. [17] synergistically combined CNNs with LSTM networks, leveraging their complementary strengths for enhanced spatiotemporal representation learning.

Recent advances in EEG-based depression detection have focused on modeling brain functional connectivity and graph representations [18]. Li et al. [19] employed functional connectivity matrices as input to CNNs for mild depression recognition. Wang et al. [20] constructed brain functional connectivity graphs using phase-locked values and utilized self-attention mechanisms to capture global temporal dependencies in EEG signals. Further advancing adaptive graph learning, Xu et al. [21] introduced a framework with dynamic agent nodes and multi-scale graph convolution for whole-brain connectivity modeling, integrating time-frequency EEG features.

These advances highlight the potential of deep learning in analyzing depression-related neurophysiological patterns. However, challenges remain in interpretability, robustness to individual variability and noise, and cross-dataset generalization. To address these issues, we propose DSEA-Net, which combines a lightweight backbone with multidimensional attention mechanisms.

III. DSEA-Net Model

A. Overall Architecture

DSEA-Net is a lightweight, end-to-end neural network architected for EEG-based depression diagnosis. As depicted in Fig. 1, the model processes raw EEG signals $\mathbf{x} \in \mathbb{R}^{1 \times C \times T}$ through a sequential pipeline that synergistically integrates multi-dimensional attention mechanisms for robust feature learning.

The Channel Attention Module first recalibrates input EEG electrodes to emphasize salient channels, then the Benchmark Network extracts initial temporal features via its temporal convolution layer.

The NeuroSE-Block core innovation incorporates depression-related neurophysiological priors by decomposing features into key frequency bands and adaptively exciting channel-wise features based on their spectral energy.

Following spectral refinement, a Depth Attention Module recalibrates features across the depth dimension. These enhanced features are then consolidated through the Benchmark Network's spatial convolution layer, before adaptive average pooling and a fully-connected layer perform classification.

In summary, DSEA-Net's lightweight backbone coherently integrates spatial, spectral, and depth-wise attentions, effectively extracting and emphasizing discriminative spatio-temporal-spectral features for accurate, interpretable depression detection.

B. Benchmark Network

The baseline network of DSEA-Net adopts the primary feature extraction architecture from DeepConvNet [8] while integrating the depthwise separable convolution technique from EEGNet [9]. The resulting feature extraction module consists of a temporal convolutional layer, a spatial convolutional layer, and employs multiple regularization methods. Depthwise separable convolution is utilized in each convolutional layer to reduce the network's parameter count.

Specifically, the temporal convolution layer uses kernels sized (21, 1, 75), where 21 is the number of kernels. Next, the spatial convolution uses kernels sized (7, C, 1), where C is the number of EEG channels. Throughout the benchmark network, the GELU activation function is applied, chosen for its smoother properties compared to ELU. Finally, to enhance adaptability to EEG data with varying sampling rates, an adaptive average pooling layer is introduced. This layer utilizes a two-dimensional pooling kernel of size (1, $k_{pooling}$), where $k_{pooling}$ is dynamically calculated per Equation (1):

$$k_{pooling} = \max\left(1, \left\lfloor \frac{f}{10/N} \right\rfloor\right) \tag{1}$$

where the operator $\lfloor\rfloor$ represents rounded down to a integer, f represents the sampling frequency of the input EEG data, and N is a scaling factor derived from the number of training samples. Based on empirical observations of EEG data characteristics, N = max(1, $\lfloor N_t/200 \rfloor$), where N_t is the number of training samples. This formulation ensures a meaningful pooling window size relative to the data's temporal scale.

The convolutional kernels decrease from 21 to 7 for two reasons: firstly, to avoid a quadratic parameter increase and overfitting in subsequent layers; secondly, because EEG signals contain richer information in the temporal than in the spatial domain.

C. Neuro-Spectral Excitation Block

Proposed for depression EEG analysis, the Neuro-Spectral Excitation Block (NeuroSE-Block) extends the Squeeze-and-Excitation paradigm by incorporating neurophysiological priors of depression biomarkers. Unlike traditional channel attention mechanisms, NeuroSE-Block explicitly models frequency-band abnormalities in EEG signals—a core pathophysiological feature of depression.

1) Multi-band Decomposition: $X \in \mathbb{R}^{D \times C \times T}$ (D=depth, C=channels, T=time) are decomposed into depression-relevant frequency bands using bandpass filters:

$$X_b = \text{Conv1D}(X; \phi_b) \quad b \in \{\theta, \alpha, \beta, \gamma\} \tag{2}$$

- θ-band (4-8 Hz): Elevated resting power in frontal midline regions, indicating cortical slowing in depression [22].
- α-band (8-12 Hz): Reduced posterior alpha rebound during attentional engagement, reflecting impaired inhibitory control [23].
- β-band (12-30 Hz): Attenuated beta rebound in ventral striatum during reward computation, associated with anhedonia [24].
- γ-band (30-45 Hz): Impaired gamma synchrony in amygdala-prefrontal circuits during emotion processing, correlating with emotional dysregulation [25].

where the convolutional kernels ϕ_b are learned during training with kernel sizes corresponding to the temporal characteristics of each frequency band. Longer kernels capture slower, low-frequency oscillations, while shorter kernels capture faster, high-frequency dynamics, allowing the model to learn optimal filters for depression detection without fixed filter banks.

2) Band Energy Extraction: Spectral energy features are extracted via spatial-temporal averaging:

$$\begin{aligned} e_b^{(d)} &= \frac{1}{C \times T} \sum_{c=1}^{C} \sum_{t=1}^{T} |X_{b,d,c,t}|^2 \\ e_b &= \left[e_b^{(1)}, \cdots, e_b^{(D)}\right]^\top \in \mathbb{R}^D \end{aligned} \tag{3}$$

Squared amplitude provides physiologically meaningful energy measurement while reducing artifact contamination.

3) Neuro-Excitation: Band energies $e \in \mathbb{R}^{D \times N_b}$ (N_b=4 bands) undergo depth feature aggregation and depression-specific weighting:

$$\bar{\mathbf{c}} = \frac{1}{D} \sum_{d=1}^{D} e_d \tag{4}$$

$$\mathbf{s}=\sigma\left(W_2\delta\left(W_1\overline{\mathbf{c}}\right)\right) \quad (5)$$

Where the weight matrices $W_1 \in \mathbb{R}^{C/16\times N_b}$ and $W_2 \in \mathbb{R}^{C\times C/16}$ form a bottleneck structure designed to enhance depression-specific feature representation: This architecture first compresses the input features to $C/16$ dimensions for improved noise robustness, then applies nonlinear transformations through ReLU and Sigmoid activation functions to generate channel-wise attention weights that selectively emphasize depression-relevant neurophysiological regions.

4) Channel Reweighting: Learned neuro-spectral weights recalibrate original features:

$$\tilde{X}_{d,c,t}=\mathbf{s}_c\cdot X_{d,c,t} \quad (6)$$

Where s_c automatically enhances channels containing depression biomarkers.

The Neuro-Spectral Excitation Block offers depression-specific benefits by modeling θ, α, β, and γ bands, enabling adaptive bandpass filtering for individual spectral variability. Its spatial localization allows attention weights to highlight neurophysiologically relevant prefrontal and temporal regions associated with depression.

IV. EXPERIMENT

A. Dataset

The study utilized data from two publicly available datasets: MODMA [26] and EDRA [27].

The MODMA dataset included a total of 53 participants, with 24 individuals diagnosed with Major Depressive Disorder(MDD) and 29 individuals without depression serving as normal controls. To assess depression, all subjects completed the Patient Health Questionnaire-9 (PHQ-9) [28] and Generalized Anxiety Disorder-7 (GAD-7) [29] with scores above 5 indicating depression. EEG signals were recorded for a duration of five minutes while the participants were in a resting state with their eyes closed. The EEG signals were captured using 128 channel electrodes placed according to the standard international 10/20 system, and the sampling frequency was set at 250 Hz.

The EDRA dataset contains EEG recordings from 50 individuals (26 high-risk, 24 low-risk), collected using a 62-electrode cap at a sampling rate of 500 Hz.

B. Data Preprocessing

To rigorously evaluate the generalizability of our model to unseen individuals—we adhered to a strict subject-independent protocol. This approach, designed to prevent any data leakage, ensures that all data from any single participant is exclusively contained within either the training, validation, or test set. The workflow comprises three key stages:

- Subject-Level Partitioning: All unique subjects were first randomly divided into 10 folds at the subject level. For each cross-validation round, folds were assigned to training, validation, and test sets in an 8:1:1 ratio (by subject count). This guarantees that the model is always evaluated on completely unseen individuals.
- Subject-Specific Preprocessing and Epoching: After subject-level splitting, each subject's EEG data was processed independently, including common average re-referencing, 1–45 Hz bandpass filtering, and ICA-based artifact removal. The cleaned data was then segmented into 5-second epochs, ensuring no subject's data appeared across different splits.
- Input Normalization: Finally, EEG epochs were normalized. Critically, the normalization parameters (mean and standard deviation) were computed exclusively from the training set and subsequently applied to the validation and test sets, preventing any information from the test data from leaking into the training process.

C. Evaluation metrics

We used multiple metrics to evaluate the performance of our proposed model, including Accuracy(ACC), Sensitivity(SEN), and Specificity (SPE)

D. Baselines

To evaluate DSEA-Net, we compared it with two classical machine learning models and seven state-of-the-art deep learning models from ten seminal studies.

SVM and MLP are classical algorithms for classifying EEG-derived depression features, but their performance heavily depends on advanced preprocessing and manual feature engineering.

Deep learning improves EEG-based depression detection by modeling brain functional graphs and capturing multi-scale spatio-temporal features, enhancing performance and providing insights into neural mechanisms.

ST-GCN [30] is a spatial-temporal graph convolutional network for the spatial topology and temporal dynamics of brain functional connectivity DeepConvNet [8] is an effective and versatile framework for deep convolutional neural networks. DeprNet [31] uses multi-layer convolutional neural network to learn EEG frequency features and detect depression. EEG-Net [9] is an EEG-based brain-computer interface framework based on a compact convolutional neural network. 1DCNN-LSTM [32] combines CNN with LSTM to capture the spatio-temporal features of EEG signals. GCTNet [20] integrates residual graph networks with Transformer encoders for joint spatial-temporal learning. These selected baselines collectively represent the forefront of research in EEG-based depression detection and underscore the critical role of fusing spatial, temporal, and spectral EEG characteristics for achieving high performance.

E. Results Analysis

In this section, we compared the performance of our DSEA-Net with baselines. As shown in Table I and Table II.

F. Ablation Experiments

We conduct ablation studies to systematically quantify the contribution of each core module in DSEA-Net. Five model variants are evaluated:

TABLE I
PERFORMANCE OF DSEA-NET AGAINST COMPARATIVE APPROACHES ON THE MODMA DATASET

Method	Acc(%)	Sen(%)	Spe(%)
SVM	70.16	71.05	69.38
MLP	73.18	83.02	63.75
ST-GCN [30]	81.26	85.41	78.32
EEGNet [9]	81.07	75.03	86.98
DeepConvNet [8]	83.41	79.88	86.69
1DCNN-LSTM [32]	89.63	90.24	89.63
DeprNet [31]	88.86	91.51	85.88
GCTNet [20]	94.17	93.63	94.58
TFAGL [21]	92.90	92.07	93.56
DSEA-Net (Ours)	**94.37**	**95.07**	**93.66**

TABLE II
PERFORMANCE OF DSEA-NET AGAINST COMPARATIVE APPROACHES ON THE EDRA DATASET

Method	Acc(%)	Sen(%)	Spe(%)
SVM	68.59	67.83	69.05
MLP	89.53	90.25	88.60
ST-GCN [30]	92.51	92.04	93.65
EEGNet [9]	94.67	92.33	93.70
DeepConvNet [8]	95.94	94.68	95.17
1DCNN-LSTM [32]	83.94	83.63	83.97
DeprNet [31]	93.94	84.01	99.40
GCTNet [20]	97.43	96.99	97.77
TFAGL [21]	95.94	94.68	95.17
DSEA-Net (Ours)	**97.33**	**98.68**	**96.06**

- **Variant a.** Benchmark Network.
- **Variant b.** DSEA-Net without Channel attention module.
- **Variant c.** DSEA-Net with standard SE Block.
- **Variant d.** DSEA-Net without Depth attention module.
- **Variant e.** DSEA-Net (our)

As shown in Fig. 2, the ablation study reveals three key findings: replacing NeuroSE with a standard SE Block causes the largest drop (ACC ↓ 8.6%), highlighting its importance. Removing Channel or Depth Attention also reduces performance (ACC ↓ 2.8% and 5.4% respectively), showing their complementary roles. Overall, combining NeuroSE, Depth, and Channel Attention enables effective spatio-temporal feature learning, improving accuracy by 15.1% over the baseline.

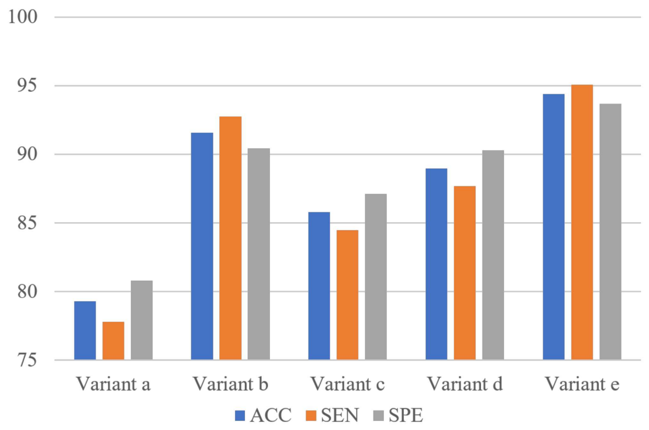

Fig. 2. Ablation study results for different modules on MODMA dataset.

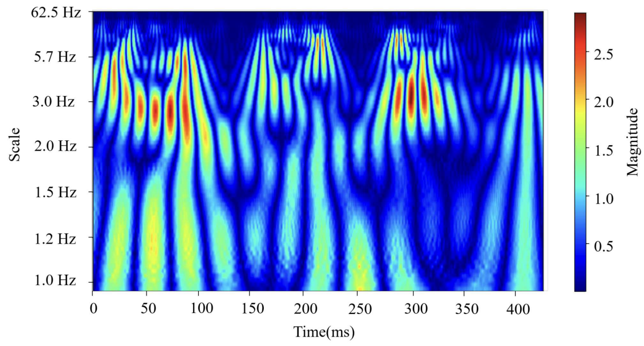

Fig. 3. Heatmap of time-frequency features.

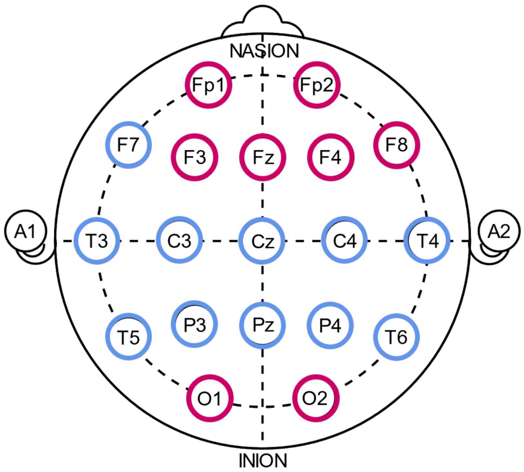

Fig. 4. Electrode distribution maps. Colored circles represent electrodes. The red circles correspond to the top 10% channels with attention weights.

G. Interpretable Feature Visualization

The electrode saliency map in Fig. 4 shows that DSEA-Net focuses on prefrontal regions, especially dorsolateral and ventromedial areas. This aligns with known prefrontal dysfunction in depression and the left-lateralized frontal alpha asymmetry, indicating reduced activity in the left prefrontal cortex.

The time–frequency analysis in Fig. 3 indicates that DSEA-Net effectively captures diagnostically relevant spectral features, with prominent and sustained θ-band (4–8 Hz) activations across the recording period. This aligns with established evidence linking increased θ power to cortical slowing and cognitive impairment in depression, suggesting that the model captures persistent neurophysiological abnormalities rather than transient artifacts. s

V. CONCLUSION

This study proposed DSEA-Net, a lightweight and interpretable EEG framework for depression detection, which synergistically integrates dynamic channel attention, neuro-spectral excitation block, and depth-wise feature recalibration. Under rigorous subject-independent validation protocols, achieves state-of-the-art performance with 97.33% accuracy on EDRA while demonstrating robust generalizability across heterogeneous EEG datasets. Notably, the derived electrode saliency maps and time-frequency features align with established clinical biomarkers of depression, providing neurophysiologically plausible interpretations and significantly enhancing the model's clinical relevance.

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