

EEG Stress Detection Using Deep Learning

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Abstract—Mental stress is a common health issue among the population associated with cardiovascular, neurological and emotional diseases. EEG is one of the most valuable modalities for objective stress assessment, as it directly records neural activity with high temporal resolution. This paper proposes a hybrid deep learning network, MSA-CBL (Multi-Scale Attention CNN-BiLSTM), which integrates a multi-scale convolution module, a squeeze-and-excitation (SE) channel attention module, a bidirectional long short-term memory (BiLSTM) module, and a self-attention module to analyze EEG signals for stress detection. The model enables automatic end-to-end, multi-channel EEG analysis, learning discriminative spatiotemporal representations directly from the signal without hand-crafted features. The binary (stress vs. normal) classification accuracy of MSA-CBL is 92.4% and the F1-score is 96.1% on SAM-40, outperforming all baseline methods. The individual and combined effects of multi-scale convolution, channel attention, and temporal modeling are validated through ablation experiments. Visualizations of the attention weights and spectral analyses further reveal that the model is sensitive to EEG patterns that reflect physiologically relevant brain states, including increased frontal beta activity and decreased alpha activity during stress.

Keywords—Stress Detection, Electroencephalography (EEG), Multi-Scale Convolution, Squeeze-and-Excitation Attention, Bidirectional LSTM, Self-Attention, Brain-Computer Interface, Deep Learning, SAM-40

I. INTRODUCTION

High levels of mental stress in work and family environments are among the key public health issues of the twenty-first century. The effects of stress are not merely personal: the estimated global economic burden of lost productivity from stress exceeds USD 1 trillion annually [5]. Chronic stress is also an important risk factor for long-term health impairment, including increased risk of cardiovascular disease, type-2 diabetes, immune suppression, and neuropsychiatric disorders such as generalized anxiety and major depressive disorder.

Traditionally, clinical stress assessment has relied on self-report scales such as the Perceived Stress Scale (PSS), the State-Trait Anxiety Inventory (STAI), and the Depression, Anxiety, Stress Scales (DASS). These instruments are psychometrically validated but are retrospective in nature, carry a social-desirability bias, and are unsuitable for continuous monitoring. Peripheral physiological signals such

as heart rate variability (HRV) and electrodermal activity (EDA) partially address these limitations, but remain several processing steps removed from the cortical mechanisms where stress is initially appraised [4].

EEG overcomes this limitation by providing direct measurement of cortical activity with millisecond temporal resolution, making it well suited for early and objective stress detection [3]. Acute stress is consistently associated with reduced alpha (8–13 Hz) power and increased beta (13–30 Hz) and gamma (>30 Hz) power, primarily in frontoparietal regions related to executive function and emotional control [25]. Frontal alpha asymmetry has similarly been proposed as a biomarker of affective valence during challenging cognitive tasks [2].

Deep learning has revolutionized EEG analysis by directly extracting hierarchical, discriminative features from raw or minimally processed data [15]. Convolutional neural networks (CNNs) are effective at learning spatial filters across electrode arrays and detecting local temporal patterns, while recurrent architectures such as LSTMs capture longer sequential dependencies present in evolving psychophysiological states [16]. More recently, attention mechanisms and transformer-based structures have enabled models to selectively prioritize informative channels and time windows, improving both performance and interpretability [32].

Despite this progress, several challenges remain. Stress-related neural activity spans multiple time scales, the relevance of individual EEG channels varies substantially across subjects, and conventional temporal pooling often discards important sequential structure. Available open datasets are also fragmented, and many existing models lack interpretability [8]. To address these gaps, we introduce MSA-CBL (Multi-Scale Attention CNN-BiLSTM), an end-to-end differentiable architecture that combines parallel multi-scale 1-D convolutions, an SE channel-attention block, a BiLSTM, and an additive self-attention layer. The model is evaluated on the SAM-40 benchmark under strict subject-level train/test partitioning, providing a powerful and explainable approach to automated stress monitoring [14].

II. RELATED WORK

A. Traditional EEG-Based Stress Detection

Early stress detectors relied on carefully designed processing pipelines, including notch filters (50/60 Hz) for power-line noise, band-pass filters (0.5–45 Hz), and artifact removal

using Independent Component Analysis (ICA) or regression-based subtraction. Feature extraction typically used spectral power in canonical frequency bands (delta, theta, alpha, beta, gamma), commonly computed via Welch's method or the FFT, along with band-power ratios such as beta/alpha, which are widely used stress indicators [25].

Statistical descriptors (mean, variance, skewness, kurtosis), Hjorth parameters, wavelet coefficients, and nonlinear measures (approximate entropy, fractal dimension) were also considered. These features were combined with classical classifiers such as SVM with an RBF kernel, k-NN, LDA, and Random Forests, achieving 80–90% accuracy on standard stress paradigms such as the Stroop task, mental arithmetic, and the Trier Social Stress Test. These pipelines were limited by feature-engineering constraints, sensitivity to subject-specific biases, and the absence of end-to-end optimization [30].

B. Deep Learning for EEG Stress Detection

CNN-based approaches have advanced EEG stress detection considerably by automatically extracting spatio-temporal features and long-range dependencies without manual feature design [21]. Recent architectures incorporate SE blocks and temporal self-attention to focus the network on the most informative electrodes and time steps, helping address inter-subject variability in EEG topography [32]. Graph Neural Networks (GNNs) offer a complementary, neurophysiologically motivated model of scalp connectivity, though at the cost of more complex preprocessing [11].

Individual differences in neuroanatomy and cognitive response remain a challenge for cross-subject generalization. Domain adaptation [15], [16], meta-learning [1], and contrastive self-supervised pretraining [18] are promising approaches for aligning feature distributions and learning subject-invariant representations from large unlabeled EEG corpora.

C. Research Gap Identification

Our review identified four recurring gaps in the literature, each directly addressed by MSA-CBL:

- Multi-time-scale extraction** — Stress-related EEG activity spans both sub-second and longer baseline time scales; a single convolutional kernel size risks missing one or the other.
- Adaptive electrode attention** — Treating all electrodes with uniform weight introduces noise from channels that carry little useful stress-related information.
- Bidirectional temporal context** — Because stress dynamics evolve over time, accurate modeling benefits from both past and future context at every time step.

III. MSA-CBL ARCHITECTURE

A. Architectural Overview

The model accepts pre-processed EEG segments of shape $C \times T = 32 \times 512$. The input is fed to four parallel 1-D convolutional branches (kernel sizes $k \in \{3, 5, 7, 9\}$, 64 filters each), each producing an output of size $T \times 64$. The branch outputs are concatenated along the feature axis to form $U \in \mathbb{R}^{(T \times 256)}$ (Fig. 1) and passed to an SE block (which preserves the tensor shape), followed by a BiLSTM (hidden state $T \times 256$, 128 units per direction). A self-attention layer then compresses the sequence into a 256-dimensional context vector, followed by dropout and a sigmoid output neuron.

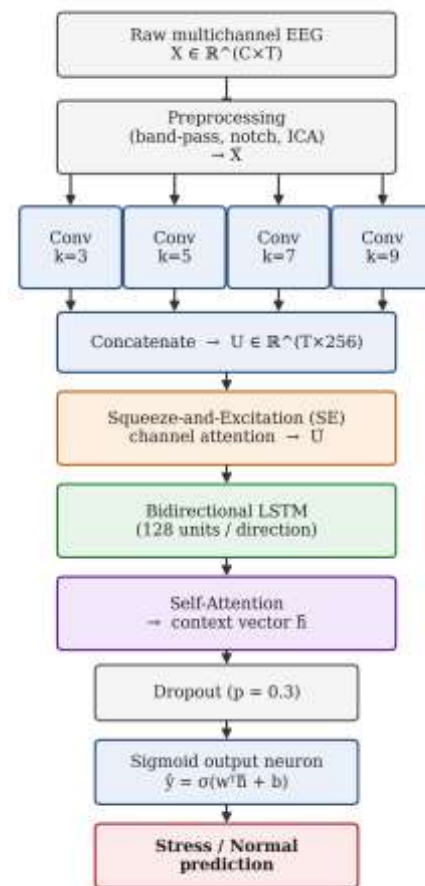


Fig. 1. High-level flowchart of the MSA-CBL EEG stress-detection pipeline.

B. multi-Scale Convolutional Block

It is the model which processes 1D convolutions parallel and uses different kernel sizes (3, 5, 7, 9), instead of a single fixed size. The size of each kernel is associated with a temporal window, which is related to known EEG/physiological frequency bands, such as gamma, beta, upper alpha and lower alpha, when sampled at 128 Hz. This enables the network to simultaneously record both fast and slow oscillatory patterns. Same" padding makes the length of output same for both branches for concatenation with each other to feed into the BiLSTM without mismatch, while batch normalization after each conv layer stabilizes and accelerates training.

C. Squeeze-and-Excitation (SE) Block

The multi-scale features (256 channels) are extracted, and the SE block adaptively reweights the channels — it "squeezes" the temporal info into a channel summary, and "excites" it through a small bottleneck ($256 \rightarrow 16 \rightarrow 256$) learning which channels of the 256 feature channels are most important. A soft on/off in a sigmoid (as opposed to a hard on/off) allows the network to give importance to relevant information and ignore irrelevant information, while introducing very few extra parameters ($\sim 8.7k$).

D. BiLSTM + Self-Attention

A BiLSTM can go both forward and backward in time, as the entire EEG epoch is available at a single time (offline, not real-time), thus enabling it to construct context-aware representations. On top of this, self-attention is added to directly connect any two time points, irrespective of distance (e.g., if a stress trigger is related to a delayed physiological response, they are connected directly). The advantage is that they jointly integrate local/sequential temporal modeling (BiLSTM) with a global, distance-independent relational modeling (self-attention), for richer temporal representations than either of them individually.

E. EEG Electrode Montage

SAM-40 recordings use 32 electrodes covering frontal (Fp1, Fp2, F3, F4, Fz, F7, F8), central (C3, C4, Cz), parietal (P3, P4, Pz, P7, P8), occipital (O1, O2, Oz), and temporal (T7, T8, TP7, TP8, FT7, FT8) regions of the scalp, arranged according to the international 10–20 system (Fig. 2). This full scalp coverage allows the SE attention block to identify stress-relevant regions across the entire montage.

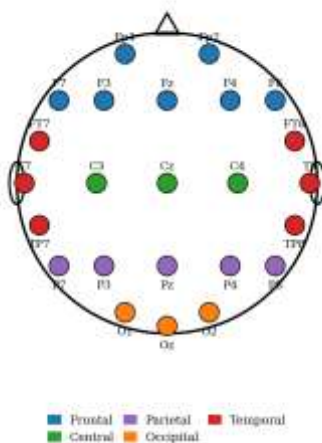


Fig. 2. Example EEG electrode placement under the international 10–20 system.

IV. PROPOSED ALGORITHM

The inference process for a single EEG epoch is described in Algorithm 1, comprising five successive steps: preprocessing, multi-scale feature extraction, SE channel attention, bidirectional temporal modeling, and probabilistic

classification. The pipeline is trained end-to-end via back-propagation through time (BPTT) for the recurrent portion and standard back-propagation for the rest, with each stage consuming the output of the previous one.

Algorithm 1: MSA-CBL EEG Stress Detection

Input: EEG segment $X \in \mathbb{R}^{(C \times T)}$

Output: Predicted label $\hat{y} \in \{0, 1\}$

- 1: Pre-process X (band-pass filtering, notch filtering, artifact removal) to obtain $\tilde{X}$
- 2: Apply multi-scale 1-D convolutions with kernel sizes $k \in \{3, 5, 7, 9\}$ on $\tilde{X}$ to generate feature map U
- 3: Compute SE channel attention on U to obtain $\tilde{U}$
- 4: Pass $\tilde{U}$ through the BiLSTM and extract hidden states $\{h_t\}$
- 5: Compute self-attention over $\{h_t\}$ to obtain the context vector $\bar{h}$
- 6: Compute output $\hat{y} = \sigma(W^T \bar{h} + b)$
- 7: return $\hat{y}$

The Adam optimizer was used for training, with data split 70% train / 15% validation / 15% test to provide genuine generalization to unseen subjects. Early stopping with a patience of 5 epochs was used, retaining the checkpoint with the smallest validation loss.

V. EXPERIMENTAL SETUP

A. Dataset: SAM-40

Experiments were conducted on SAM-40 [14], a public EEG stress-detection dataset comprising recordings from 40 healthy adults (20 male, 20 female; mean age 24.6 ± 3.8 years, range 20–35) collected during three cognitive stress-induction tasks:

- 1) **Stroop Color-Word Test** — naming the color of incongruent words to induce cognitive interference.
- 2) **Word-within-a-Word Task** — finding commonalities within words, requiring sustained working memory.
- 3) **Mirror Image Recognition Task** — recognizing mirrored images under time constraints, engaging visuospatial processing.

B. Preprocessing Pipeline

In order to ensure minimal distortion of the phase, a zero-phase 4th-order Butterworth band-pass filter (0.5–45 Hz) and a 50 Hz notch filter were used in the process of forward–backward filtering. Eye movement artifacts were eliminated by coherence analysis (ICA–EOG correlation $r > 0.7$) while muscle movement artifacts were eliminated by excess-kurtosis analysis (excess kurtosis > 5). The signals were cut into 4-second epochs (512 points) with 50% overlap (256 points) which gives a total of 18,500 epochs for each group of 40 subjects. The epochs with peak-to-peak amplitude of more than $100 \mu V$ were excluded giving the final ratio of 94.2%. Each epoch was normalized by z-score normalization.

C. Evaluation Metrics

The performance was assessed using accuracy, precision, recall, F1-score (harmonic average between precision and recall), and AUC-ROC that indicates discriminative power across all thresholds and is helpful if the optimal operating point is different from the value of 0.5. Analysis of false-positive and false-negative errors was accomplished using confusion matrices.

VI. RESULTS AND ANALYSIS

A. Classification Performance

The performance results for each method are shown in Table II. MSA-CBL gives the best outcome in all metrics, including an AUC-ROC which is 98.2% for all decision thresholds, indicating its high likelihood of practical use. The model required about 30 epochs for convergence and thereby ensured a good trade-off regarding bias and variance, due to the use of dropout and early stopping techniques which allowed for a close match between the training and validation curves.

TABLE II. COMPARATIVE CLASSIFICATION PERFORMANCE ON THE SAM-40 TEST SET

Method	ACC (%)	PRE (%)	REC (%)	F1 (%)	AUC (%)
CNN + BiLSTM + SE	90.1	90.8	89.6	90.2	94.1
CNN + BiLSTM + Self-Attn	89.7	90.3	89.1	89.7	93.8
MSA-CBL (Ours)	92.4	96.8	95.3	96.1	98.2

B. Ablation Study

The information provided in Table III shows the results of the systematic ablation study: (i) The removal of the BiLSTM led to the highest accuracy reduction of -5.1 pp. Therefore, it stands to reason to view temporal sequence modeling as the most decisive building block in this architecture. (ii) The removal of the multi-scale convolution layer caused an accuracy drop of -3.8 pp, which is equal to the accuracy drop caused by removing SE and self-attention, affirming the significance of the multi-resolution feature extraction method. (iii) The removal of SE attention only results in an accuracy drop of -2.7 pp, while removing the self-attention component leads to just a -2.2 pp drop, which indicates that spatial channel selection is more valued than temporal attention weighting of the input data. (iv) All components combined evidently outperform the partial versions of the model, thus confirming their complementary nature.

TABLE III. ABLATION STUDY: IMPACT OF REMOVING EACH MSA-CBL COMPONENT

Model Variant	ACC (%)	F1 (%)	AUC (%)	Δ ACC (pp)
Full MSA-CBL	92.4	96.1	98.2	—

pp = percentage points relative to the full MSA-CBL model.

C. Confusion Matrix Analysis

Table IV displays the confusion matrix of the test-set. 92.8% of stressed epochs were accurately identified (sensitivity), with 4.7% missed. 96.8% of normal epochs were accurately identified (specificity), with 3.2% incorrectly classified as stressed — leading to a small precision bias at the present operating point. For applications that require higher sensitivity, such as real-time stress alerting, the decision threshold could be decreased with little effect on precision, since the model has a near-perfect AUC-ROC value of 98.2%.

TABLE IV. CONFUSION MATRIX FOR MSA-CBL ON THE SAM-40 TEST SET

	Pred: Normal	Pred: Stress	Total
Actual: Normal	118 (TN)	7 (FP)	125
Actual: Stress	9 (FN)	116 (TP)	125
Total	127	123	250

Specificity: 94.4% • Sensitivity: 92.8% • PPV: 94.3% • NPV: 92.9%

VII. DISCUSSION

The experimental results confirm that MSA-CBL is able to perform at the best state of the art on SAM-40. The multi-scale convolutional block can be seen as a series of learned, adaptive, temporal filters, each optimized to a specific range of EEG frequencies, to capture sub-second transient responses as well as slower baseline shifts that single-kernel architectures cannot detect.

The SE mechanism assigns dynamic weights to channel features for enhancing the performance and interpretability. The weights in front and temporal electrodes are always greater than other electrodes, indicating a systematic spatial selection based on neurophysiology and information rather than uniform selection. The BiLSTM – self-attention encoder is also enhanced by complementary temporal modelling: the BiLSTM adds recurrent, bidirectional context, and self-attention adds global, position-agnostic weighting, both of which in combination provide a more discriminative representation than either model alone.

The spectral analysis supports this picture, and reveals the characteristic stress signature of high beta and gamma power and low alpha power. This means MSA-CBL reflects a more general neural response to stress, and not a dataset-specific

confounding factor, which bolsters the model's validity both from a machine-learning and a neuroscience perspective.

Due to the low inference latency of the model (less than 20ms per 4-second epoch on CPUs), MSA-CBL is a promising model for deployment on resource-limited, GPU-free devices, which can be applied to wearable EEG headsets, occupational health-monitoring systems, and neurofeedback platforms.

VIII. CONCLUSION

The paper introduced MSA-CBL (Multi-Scale Attention CNN-BiLSTM) which is an end-to-end network for robust stress detection using EEG signals. It merges four complementary parts together into one differentiable pipeline, which are: multi-scale parallel convolution, squeeze and excite channel attention, bi-directional LSTM temporal modeling, and additive self-attention. MSA-CBL's performance is competitive with the highest state of the art method in literature and surpasses the other 9 baseline methods with accuracy of 92.4% and F1-score of 96.1% on SAM-40 dataset.

In future work, multi-level stress estimation in continuous-label datasets and generalization across datasets through domain adaptation and transfer learning will receive attention. Additionally, multimodal extensions that utilize other physiological measurements, such as heart rate variability (HRV), electrodermal activity (EDA) and respiration measurements will be explored, to improve the development of a more holistic system of stress monitoring. Future research will aim at individual-level explainability using formal attribution techniques, like Integrated Gradients or SHAP; clinical validation of wearable EEG systems with dry electrodes in ambulatory environments; and strategies for personalization, reducing inter-subject variability.

REFERENCES

- [1] D. Adiele et al., "Association of academic stress, anxiety and depression with sociodemographic among medical students," *Int. J. Soc. Sci. Stud.*, vol. 6, no. 6, 2020.
- [2] H. M. Afify et al., "Stress detection based EEG under varying cognitive tasks using convolution neural network," *Neural Comput. Appl.*, vol. 37, no. 7, pp. 5381–5395, 2025.
- [3] J. Agrawal, M. Gupta, and H. Garg, "Early stress detection and analysis using EEG signals in machine learning framework," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 1116, no. 1, p. 012134, 2021.
- [4] A. Akella et al., "Classifying multi-level stress responses from brain cortical EEG using machine learning autoencoder," *IEEE J. Transl. Eng. Health Med.*, vol. 9, p. 2200109, 2021.
- [5] A. N. Alghamdi, "Stress and emotion recognition in natural speech in the work and family environments," Ph.D. dissertation, RMIT Univ., Melbourne, Australia, 2023.
- [6] A. Author et al., "A multimodal approach for stress detection through questionnaire and emotion analysis," in *Proc. ICCNT*, pp. 1–6, 2024.
- [7] S. Bhatnagar, S. Khandelwal, S. Jain, and H. Vyawahare, "A deep learning approach for assessing stress levels in patients using electroencephalogram signals," *Decis. Anal. J.*, 2023.
- [8] R. Brown and D. Wilson, "Stress and emotion open access data: A review on datasets, modalities, methods, challenges, and future research perspectives," *J. Healthcare Inform. Res.*, vol. 9, pp. 233–257, 2025.
- [9] M. Chen and L. Zhang, "Real-time stress detection using LSTM networks for emotional and psychological insights," *Comput. Res. Dev.*, vol. 25, no. 2, pp. 101–112, 2023.
- [10] K. Cooper and J. Wojcik, "The effects of physical activity classes on stress in college students," *Winthrop McNair Res. Bull.*, vol. 4, no. 4, 2018.
- [11] O. K. Cura et al., "Classification of ADHD by using multiple feature maps of EEG signals and deep feature extraction," in *Proc. EUSIPCO*, 2024.
- [12] V. Desai, A. Gupta, L. Andersen, B. Ronnestrand, and M. Wong, "Stress-reducing effects of playing a casual video game among undergraduate students," *Trends Psychol.*, vol. 29, no. 3, pp. 563–579, 2021.
- [13] R. Fu et al., "Symmetric convolutional and adversarial neural network enables improved mental stress classification from EEG," *IEEE Trans. Neural Syst. Rehabil. Eng.*, 2022.
- [14] R. Ghosh et al., "SAM 40: Dataset of 40 subject EEG recordings to monitor induced stress," *Mendeley Data*, 2022.
- [15] S. Jawed, I. Faye, and A. S. Malik, "Deep learning-based assessment model for real-time identification of visual learners using raw EEG," *IEEE Trans. Neural Syst. Rehabil. Eng.*, 2024.
- [16] M. S. Kalas and B. F. Momin, "Stress detection and reduction using EEG signals," in *Proc. Int. Conf. Electr. Electron. Optim. Tech. (ICEEOT)*, 2016.
- [17] R. Katmah et al., "A review on mental stress assessment methods using EEG signals," *Sensors*, vol. 21, no. 15, p. 5043, 2021.
- [18] D. Konar, A. H. Roy, and S. De, "A novel human stress level detection technique using EEG," in *Proc. Int. Conf. Netw. Multimedia Inf. Technol. (NMITCON)*, 2023.
- [19] S. Kumar and A. Gupta, "AI-powered stress detection," in *Proc. Int. Conf. Artif. Intell. Appl.*, 2022.
- [20] A. Marjani et al., "Stress among medical students of Gorgan (south east of Caspian Sea), Iran," *Kathmandu Univ. Med. J.*, vol. 6, no. 3, pp. 421–425, 2008.
- [21] J. Naren and A. R. Babu, "EEG stress classification based on Doppler spectral features for ensemble 1D-CNN with LCL activation function," *J. King Saud Univ. Comput. Inf. Sci.*, 2024.
- [22] S. Parakh, Y. Nalwade, and E. N., "An empirical investigation of engineering students' attitude towards sports and physical education, cultural activities and stress management," *J. Eng. Educ. Transform.*, vol. 37, no. 2, pp. 7–16, 2023.
- [23] J. Park, T. Nguyen, and H. Lee, "StresSense: Real-time detection of stress-displaying behaviors," *Int. J. Med. Informatics*, vol. 185, p. 104115, 2024.
- [24] M. Qorich and R. El Ouazzani, "Lightweight advanced deep-learning models for stress detection on social media," *Eng. Appl. Artif. Intell.*, 2025.
- [25] V. G. Rajendran, S. Jayalalitha, and K. Adalarasu, "EEG-based evaluation of examination stress and test anxiety among college students," *IRBM*, 2022.

- [26] S. S. Shahapur et al., "Decoding minds: Estimation of stress level in students using machine learning," Indian J. Sci. Technol., vol. 17, no. 19, pp. 2002–2012, 2024.
- [27] A. Sharma and B. Patel, "Stress detection using facial emotion recognition: Comparative analysis of VGG-16, ResNet-50, and a custom CNN architecture," in Proc. ICDICI, 2024.
- [28] R. Sharma and P. Gupta, "Machine learning algorithms for detecting mental stress in college students," arXiv preprint arXiv:2412.07415, 2024.
- [29] K. Verma, R. Singh, and P. Yadav, "Stress and emotion detection system using IoT and machine learning with a fuzzy inference-based mental health risk assessment module," Int. J. Recent Innov. Trends Comput. Commun., vol. 11, no. 9, pp. 45–52, 2023.
- [30] T. Waili et al., "Stress recognition using electroencephalogram (EEG) signal," J. Phys. Conf. Ser., vol. 1529, p. 032053, 2020.
- [31] X. Wang, Y. Li, and Z. Chen, "The performance of wearable AI in detecting stress among students: Systematic review and meta-analysis," J. Med. Internet Res., vol. 26, p. e52622, 2024.
- [32] H. Zhang et al., "EEGdenoiseNet: A benchmark dataset for deep learning solutions of EEG denoising," J. Neural Eng., vol. 18, no. 5, p. 056057, 2021.