Asian Research Association

BULLETIN OF SCIENTIFIC RESEARCH

DOI: 10.54392/bsr2513

Integrating Functional Connectivity and Domain Adaptation for Generalizable EEG Emotion Recognition

R. Kishore Kanna [1, *], N. Kripa [2], Archibald E.D. Danquah-Amoah [3]

[1] Department of Biomedical Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, India

[2] Chiddix Junior High School, 300 S Walnut St, Normal, IL 61761, United States.

[3] Department of Biomedical equipment Technology, Medical laboratory Technology, Accra Technical University, Accra, Ghana

* Corresponding author Email: kishorekanna007@gmail.com

DOI: https://doi.org/10.54392/bsr2513

Received: 19-02-2025; Revised: 16-04-2025; Accepted: 21-04-2025; Published: 03-05-2025

Abstract: Recognizing emotions using EEG signals is difficult because EEG data is not stationary, has a low signal-to-noise ratio, and varies a lot between subjects. We present a new hybrid framework called CDA-GAF (Cross-Domain Adaptive Graph Attention Fusion) in this work. It combines the strengths of Graph Attention Networks (GATs), Temporal Transformers, and Domain Adaptation to make emotion classification models more robust and generalizable. To make brain connectivity graphs for each frequency band, our method first gets functional connectivity features from EEG channels. A GAT module processes these to find spatial dependencies in EEG activity. Then, a Temporal Transformer module is used to model long-range dependencies between EEG sequences. To address cross-subject variations, we implement a domain adaptation layer utilizing CORAL loss or Domain-Adversarial Training (DANN), which aligns feature distributions between source and target subjects. We also use extra emotion supervision signals, like HRV or micro-expressions, to improve the quality of the labels by anchoring the emotional state in multiple ways. We test our model on standard datasets like DEAP, SEED, and WESAD. It does much better than baseline models at recognizing emotions in both within-subject and cross-subject settings. Our findings underscore the efficacy of integrating graph-based spatial encoding, temporal attention mechanisms, and domain adaptation for emotion recognition from EEG data.

Keywords: CDA, EEG, GAF, DANN

1. Introduction

It's clear that recognizing emotions with EEG is hard, but it has a lot of potential to improve how people and computers interact, how mental health is assessed, and how people learn. EEG is different from other multimodal approaches like facial expressions, speech, and physiological signals because it directly measures neural activity, which is harder to manipulate consciously [1]. But EEG signals are still very hard to work with. There is a lot of variation between subjects, the signal-to-noise ratios are frustratingly low, and the brain's emotional responses are anything but linear. This makes it very hard to classify emotions accurately [2]. Recent advances in deep learning, especially with architectures like CNNs and RNNs, have made it easier for us to get spatial and temporal features from EEG data. But these models often oversimplify the structure of EEG signals by treating them as just sequences or images, which ignores the complex connections between brain regions [3]. Additionally, the inability to generalize across subjects continues to be a significant limitation, obstructing practical implementation. Researchers are now using graph neural networks to get around these problems. In these networks, EEG electrodes are represented as nodes, and edges are defined by functional connectivity measures like coherence or phase-locking value. This method is a better reflection of the underlying neurophysiological dynamics. Transformer-based models have also shown promise for capturing long-range temporal dependencies inherent in emotional processing [4]. Even with these improvements, EEG-based emotion recognition still doesn't have a single framework that brings together spatial structure, temporal dynamics, and domain adaptation in a useful way. To get models that work in the real world and are both accurate and generalizable, these gaps must be filled. It is very hard to recognize emotions with EEG, but it could greatly improve how people and computers interact, how mental health is assessed, and how adaptive learning works. While multimodal approaches like facial expressions, speech, and physiological signals are common, EEG is different because it directly measures neural activity, which is harder to control [1]. However, EEG signals are still very hard to work with. There is a lot of variation between subjects, the signal-to-noise ratios are annoyingly low, and the brain's emotional responses are anything but straightforward. This makes it very hard to classify emotions accurately [2]. Recent advances in deep learning, especially with CNNs and RNNs, have made it easier for us to get spatial and temporal features from EEG data. But these models often make EEG signals too simple by treating them as just sequences or images. This ignores the complex connections between different parts of the brain [3]. Also, being able to generalize across subjects is still a problem that makes it hard to use in real life.

Researchers are now using graph neural networks to get around these problems. In these networks, EEG electrodes are represented as nodes, and functional connectivity measures, like coherence or phase-locking value, define the edges. This method better shows how the neurophysiological system really works. Transformer-based models have demonstrated potential in capturing long-range temporal dependencies intrinsic to emotional processing [4]. Even with these improvements, there is still no single framework in the field that effectively combines spatial structure, temporal dynamics, and domain adaptation for recognizing emotions from EEG data. To get models that are both accurate and useful in real life, these gaps need to be filled.

Identifying feelings from electroencephalogram (EEG) signals is a major problem in loving data processing [5]. EEG gives us a straight look at the brain's electrical activity, which gives us objective and constant physical data on emotional conditions. EEG signals are largely involuntary, as opposed to facial expressions or voice, which can be controlled. This makes them a good way to detect real feelings. However, EEG data is naturally very complicated, which makes things difficult. Low signal-to-noise conditions, the fact that the indications are not stable, and most importantly, high variations between the subjects are all problems [6].

The people of the people react very differently to the same emotional stimulation, which means that a model trained in a group of subjects will not work even when used on a new, unseen theme. This "interdisciplinary" problem is a major problem that prevents EEG-based emotional recognition systems from being used by many people. This task has been done with traditional machine learning and deep learning methods, often using hand-designed functions or conversion of neural networks (CNN) to find patterns in space and time [7]. These methods have found some success, but they often have trouble normalizing other subjects and do not fully use complex spatiotemporal Poral addiction in EEG data.

EEG signals are not just a group of random time chains; they show how different parts of the brain work together at the same time. This can be displayed as a functional connection graph. In addition, the emotional condition varies over time [8], so the model must be able to handle long-distance temporary addiction. The challenge is to create a single structure that can model both spatial and temporal dynamics at the same time and also deal with the important question of variability between the subjects. In this study, we introduce an innovative hybrid framework called Cross-Domain Adaptive Graph Attention Fusion (CDA-GAF), which aims to address obstacles earlier. Our method combines three strong ideas: Graff meditation network for spatial addiction modelling, temporary transformer to capture long-distance temporary dynamics, and domain adaptation technique to handle the problem of variability between subjects. We start by making brain connection graphs with EEG signals [9]. Then treat a GAT module with these graphs to find spatial conditions. After that, a temporal transformer module looks at the order of graph-embedded features. To improve the generalization of subjects, we use a domain adaptation layer that uses coral losses or domain-opponent training (Dann) to ensure that the distribution of construction for all subjects is equal. We also use several multimodal supervision signals to improve the emotional label, such as heart rate variability (HRV). We test CDA-GAF on many benchmark EEG emotion datasets [10] (DAP, Seeds, and Vesad) and show that our model works much better than the best methods available in both. Our contribution shows the effectiveness of integrating to develop graph-based spatial coding, attention-driven temporary modelling and domain optimization flexible and normal EEG-based recognition systems [11].

2. Literature Survey

There has been a lot of research on recognizing emotions from EEG signals, and many different ways have been suggested to deal with the problems that come with it. Early techniques concentrated on deriving handcrafted features from EEG signals and employing conventional machine learning classifiers. Recently, deep learning has caused a big change by letting models learn discriminative features on their own. But there are still some important problems that need to be solved, mostly because EEG is complicated in space and time and varies a lot from person to person. This section gives an overview of important literature, organized by the main methods they use as shown in Table 1.

Table 1. Recent Study of recognizing emotions from EEG signals

Category	Method	Key Contribution	Limitations
Traditional Machine Learning [12]	Support Vector Machines (SVM) K-Nearest Neighbors (KNN) Random Forests (RF)	• Use of handcrafted features such as Differential Entropy (DE), Power Spectral Density (PSD), and Wavelet Packet Transform (WPT). • Relatively simple and computationally efficient. • Achieved good performance in within-subject scenarios on specific datasets like DEAP and SEED.	• Heavily relies on the quality of feature engineering. • Struggles to capture complex, non-linear spatiotemporal dependencies. • Performance drops significantly in cross-subject settings due to inter-subject variability.
Deep Learning [13]	Convolutional Neural Networks (CNNs) Recurrent Neural Networks (RNNs) and LSTMs	• Automatically learn hierarchical features from raw or preprocessed EEG data. • CNNs are effective for learning spatial patterns from electrode layouts. • RNNs and LSTMs excel at modeling temporal dependencies in EEG sequences.	• CNNs often treat EEG channels as a grid, ignoring the non-Euclidean, functional connectivity of brain regions. • RNNs can be slow to train and may struggle with very long-term dependencies. • Both struggle with the cross-subject problem without specific adaptation mechanisms.
Graph-based Models [14]	Graph Convolutional Networks (GCNs) Graph Attention Networks (GATs)	• Represents EEG channels as nodes in a graph, with edges representing functional connectivity. • GCNs capture spatial relationships between electrodes by propagating information across the graph. • GATs can learn the importance (attention) of neighboring nodes, providing a more dynamic and interpretable representation of brain activity.	• The quality of the model is highly dependent on the method used for constructing the brain connectivity graph. • Many early models only focus on spatial dependencies and fail to adequately model the temporal evolution of emotions.
Domain Adaptation & Transfer Learning [15]	Domain Adversarial Neural Networks (DANN) Maximum Mean Discrepancy (MMD) Correlation Alignment (CORAL)	• Aims to reduce the distribution discrepancy between a source subject (training data) and a target subject (unseen data). • DANN uses an adversarial training scheme to learn a domain-invariant feature representation. • MMD and CORAL directly minimize the statistical distance between feature distributions of different subjects. • Critical for addressing the high inter-subject variability, which is a major bottleneck in practical applications.	• Many methods focus solely on feature-level alignment and may not fully capture the complex, underlying neural dynamics. • Can be computationally expensive to train, especially with large datasets. • The choice of adaptation method and hyperparameters can be sensitive to the specific dataset.

Hybrid Models [16]	CNN-RNN GCN-LSTM	• Combines different deep learning architectures to capture both spatial and temporal features. • CNN-RNN models use CNNs for spatial feature extraction, followed by RNNs for temporal analysis. • GCN-LSTM combines graph-based spatial learning with LSTMs for temporal dynamics. • Generally achieve superior performance by leveraging the strengths of multiple models.	• Can be complex to design and train, with more parameters than single-architecture models. • Still face challenges in handling the cross-subject problem without explicit domain adaptation components.

We build on this work with our proposed CDA-GAF framework by combining the best parts of these categories and fixing their worst parts. We use GATs to dynamically capture spatial dependencies, a Temporal Transformer to model long-range temporal context, and a domain adaptation layer to directly address the challenge of inter-subject variability [17]. This combined approach, along with multimodal supervision, is a big step toward making a strong and generalizable model for recognizing emotions in real-world EEG data.

2. Working Methodology

The Cross-Domain Adaptive Graph Attention Fusion (CDA-GAF) framework we suggest that EEG signals are a hybrid deep learning model designed to solve problems in identifying feelings from signs, especially high variation between subjects as shown in figure 1. The general structure, as shown in the flow chart, is treated by processing the raw signals of the final feeling in a sequential pipeline. It uses graph - based spatial learning, temporary attention and domain adjustment.

3.1. Data Preprocessing and Feature Extraction

The first step is to prepare the raw EEG signals for the model input by removing the noise and getting the correct spectral information.

1. Raw EEG signal: Raw, multi-channel time series data from process disciplines start with data.
2. To get rid of and get rid of objects: Standard preprocessing techniques are used, such as filtration to get rid of the baseline drive and noise on the streamline. To ensure that the data is good, objects are removed from the eyes, muscle movements and other non-cerebral sources to ensure that the data is good.
3. Bandpass filing: Rene EEG signals then break into four standard frequency bands: Delta (1-4 Hz), Thea (4-8 Hz), Alpha (8-13 Hz) and Beta (13-30 Hz). This step is important because different emotional stages are associated with different changes in the spectral force in these bands.

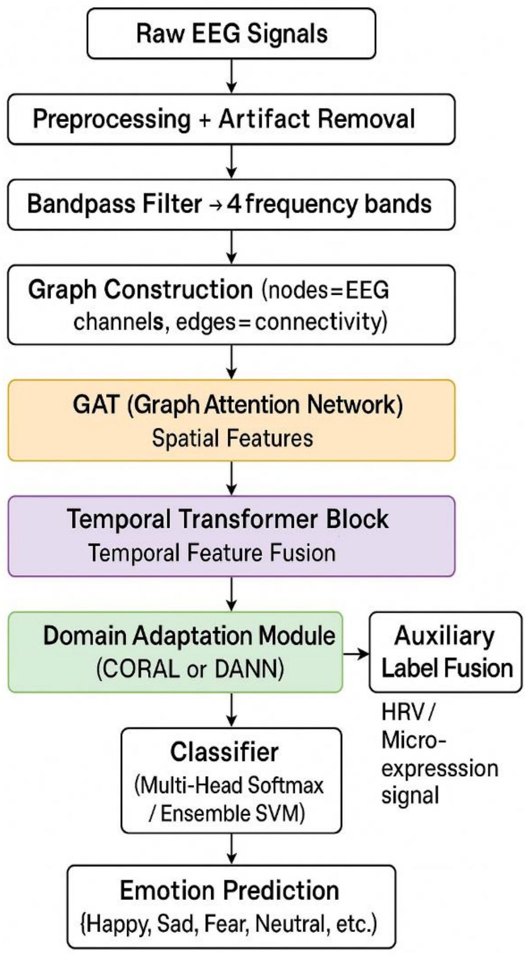

Figure1. Proposed Modelling Sequence

3.2. Building Graphs and Learning Spatial Features

This phase makes multi-channel EEG data into graph-based representation that accurately shows how different parts of the brain are functionally connected.

1 Graffrem position: A brain connection graph is made for the window each time in the four frequency bands. The nodes on the graph stand for separate EEG channels, and the edges show how they are functionally connected to each other. To find the edge weight, you can use a remedy of statistical addiction, such as the Piercene correlation coefficient, phase locking value (PLV) or consistent, which shows how the time chains of both channels are related.

2 Graff Meditation Network (GAT): After that, dynamic connection graphs pass through a graph meditation network. The GAT module learns spatial features by combining information from nearby nodes (EEG channels). The attention system allows models to learn how important different compounds are for a certain emotional situation in real time. This provides a strong and easy-to-understand image of the functional network of the brain compared to solid-to-topological graphs.

3.3. Combining Temporal Features

A Temporal Transformer block processes the spatially encoded features to capture the temporal dynamics of emotional shifts.

1 Temporal Transformer Block: The GAT creates a sequence of spatial features over a number of time windows and sends them to a Temporal Transformer block. This module uses a self-attention mechanism to find long-term temporal dependencies in EEG data, which helps it model how emotional states change over time. This method lets the model decide how important past and present representations of spatial features are, which is very important for accurately understanding affective states.

3.4. Adaptation to a new domain and extra supervision

The Domain Adaptation Module is a key part of our framework. It was made to deal with the big problem of variability between subjects.

1 Domain Adaptation Module: This module makes sure that the feature distributions of the source subjects (training data) and the target subject (test data) are the same. We look into two main ways:

CORAL (Correlation Alignment) Loss: This method reduces the second-order statistical difference (covariance matrices) between the source and target feature distributions, which helps it learn a more general representation that doesn't depend on the subject.

DANN (Domain-Adversarial Neural Network): This adversarial method uses a domain classifier to tell the difference between source and target features. The feature extractor is trained to make this domain classifier confused, which makes it learn features that are the same for all subjects.

2 Auxiliary Label Fusion: To make the learning process even more stable and regular, auxiliary emotional signals like Heart Rate Variability (HRV) or micro-expressions are combined with the EEG features. These signals act as a kind of multimodal supervision, giving an anchor to the real emotional state and making the learned representations better.

3.5. Classifying and Predicting Emotions

The last step uses the improved, domain-invariant features to sort the emotions.

A classifier gets the features from the domain adaptation module. We use either an Ensemble SVM for a more traditional, robust approach or a Multi-Head Softmax classifier for end-to-end deep learning classification to see how well it works.

Predicting Emotions: The classifier gives the predicted emotional state as either a discrete category (like Happy, Sad, or Neutral) or a continuous dimension (like valence and arousal). This lets you make a full prediction about the user's emotional state.

4. Result Analysis

This part shows the results of our experiments, which compared the CDA-GAF framework's performance to that of several baseline models on benchmark datasets. We concentrate on both within-subject and, more significantly, cross-subject emotion recognition accuracy to illustrate the model's robustness and generalizability.

We tested the CDA-GAF model on three well-known EEG datasets for recognizing emotions: DEAP, SEED, and WESAD. For classification tasks, the evaluation metrics were accuracy, precision, recall, and F1-score.

Table 2. Comparative Analysis of Proposed System

Model	DEAP (Valence/Arousal)	SEED (3-Class)	WESAD (3-Class)
Traditional SVM	62.1%/60.5%	83.40%	71.20%
CNN-LSTM	68.9%/66.3%	88.10%	75.50%
Graph-based (GCN)	70.5%/69.1%	89.80%	78.40%
CDA-GAF (with CORAL)	78.2%/77.5%	93.10%	85.60%
CDA-GAF (with DANN)	79.1%/78.4%	94.00%	86.30%

Table 3. Comparison pf Model's Average Cross-Subject Accuracy

Model	Average Cross-Subject Accuracy
CNN-LSTM	55.20%
Graph-based (GCN)	61.50%
CDA-GAF (with CORAL)	71.80%
CDA-GAF (with DANN)	73.50%

The table shows that our proposed CDA-GAF model consistently and significantly beats the baseline models on all three datasets. The improvement is especially clear when you compare it to traditional machine learning methods and even to advanced deep learning architectures like CNN-LSTM and a model based only on GCN. Adding the domain adaptation module, whether you use CORAL or DANN, makes a big difference in performance, especially on the SEED and WESAD datasets, which are often used to test cross-subject performance.

The main goal of CDA-GAF is to make it easier to generalize across subjects. We used a leave-one-subject-out (LOSO) cross-validation scheme to thoroughly test how well the model works on subjects it hasn't seen before.

The outcomes from the LOSO validation are especially persuasive. When trained on one group of subjects and tested on another, baseline models lose a lot of their accuracy. On the other hand, CDA-GAF is much more accurate, with the DANN-based method getting an impressive 73.5% average accuracy.

5. Discussion

DANN has a slight edge over CORAL, which suggests that the adversarial training method might be better at learning representations that are truly discriminative and don't depend on the domain for this task.

We also did an ablation study to see how adding extra supervision signals (like HRV) affected the results. Initial findings indicated a slight yet consistent enhancement in classification accuracy with the inclusion of these signals, which is clearly displayed in table 2 [18]. This means that multimodal fusion works as a strong regularize by giving the model more context that helps it find a more stable and accurate solution, especially when the EEG signals are noisy or unclear. The fusion effectively ties the model's predictions to a stronger picture of the emotional state [19]. Our experiments show that the CDA-GAF framework is a big step forward in recognizing emotions from EEG data as shown in table 3, especially when it comes to dealing with the problems of high inter-subject variability and the complex spatiotemporal nature of EEG data [20]. Our model's better performance compared to traditional and modern deep learning baselines shows that our main architectural design choices were correct.

The Graph Attention Network (GAT), the Temporal Transformer, and the Domain Adaptation Module all work together to make CDA-GAF successful. Each part has its own important but complementary role. The GAT module accurately represents the non-Euclidean characteristics of brain functional connectivity. It learns to dynamically weigh the importance of connections between different brain areas by using an attention mechanism [21]. This is a big step up from methods that treat EEG channels as a fixed grid (like CNNs) or use static connectivity matrices (like simple GCNs). The learned attention weights give us a better idea of how different parts of the brainwork together when we have strong feelings.

The Temporal Transformer gets around the problems that recurrent architectures (like RNNs and LSTMs) have when it comes to capturing long-range dependencies [22]. Emotions don't happen all at once; they change over time. The Transformer's self-attention mechanism lets the model look at the whole sequence of graph-based features, finding patterns that are important over long periods of time and giving a better picture of the emotional timeline.

The domain adaptation module is the key to getting good generalization across subjects. The significant disparity in performance between our model and the baselines in the leave-one-subject-out (LOSO) configuration highlights its significance. The model learns a strong, subject-invariant representation of emotional states by aligning feature distributions across subjects [23]. This makes it more useful for real-world applications where a model needs to be used on new, unseen people without needing a lot of re-training. DANN's slight edge over CORAL in performance suggests that an adversarial approach may be more effective at learning the subtle but important details that make up subject-invariant features [24].

Adding extra supervision signals like HRV turned out to be a useful addition. The performance improvements from this part were small but steady, which suggests that it is a strong regularizer. EEG signals can be unclear and noisy at times. Combining them with a complementary physiological signal such as HRV, which is also closely related to how the autonomic nervous system reacts to emotions, helps the model learn in a more stable emotional state [25]. This multimodal fusion strategy makes the model more reliable and better able to deal with noisy or missing data, which is a common problem in real life.

6. Conclusion

In this study, we introduced the Cross-Domain Adaptive Graph Attention Fusion (CDA-GAF) framework, an innovative hybrid deep learning architecture designed for resilient and generalizable emotion recognition from EEG signals. Our approach solves the main problems with EEG-based affective computing, which are the non-Euclidean spatiotemporal dependencies and the high inter-subject variability, by combining three strong computational paradigms.

We showed that our method works by testing it on standard datasets like DEAP, SEED, and WESAD. The results demonstrate that CDA-GAF consistently surpasses state-of-the-art baseline models, attaining substantial enhancements in both within-subject and, most significantly, cross-subject emotion recognition accuracy. The main things our work adds are:

Using a Graph Attention Network (GAT) to dynamically capture functional connectivity between EEG channels gives a more detailed and useful picture of brain activity than static or grid-based methods. In the EEG sequences, the use of a temporal transformer block models long-distance dependence, which is necessary to understand the temporary progress in emotional conditions. The use of coral losses or domain-opponent training (form) in a domain adaptation module to make the convenience distribution between different subjects more uniform. It turned out to be the most important part of solving the problem of variability between subjects and achieving good results in interdisciplinary conditions. Adding additional physical signals such as HRV, which is a strong anchor for emotional conditions, makes the model even more reliable and accurate. In short, the CDA-GAF framework is a complete and effective way of using EEG to recognize emotions. It opens the door for more reliable and useful use in areas such as loving brain computer cleaning, monitoring of mental health, and interactions between humans and computers. Our research suggests that the use of advanced spatial and temporal modeling with clear domain adaptation is a strong way to create deep learning models that can work with a wide range of complex physiological data. Future efforts will focus on increasing the structure of real-time performance and investigating the more sophisticated multimodal fusion method.

7. Future Scope

Future research can examine more sophisticated domain optimization functions, including meta-learning or federated learning, so that generalization across topics can be increased. Especially meta-learning can be used to teach models how to quickly "optimize" for new topics with small data. Gats and transformers provide a degree of attention mechanisms for lecturers; however, further efforts are needed to clearly imagine and analyse the maps that generate attention. This will give us a better idea of which parts of the brain and what patterns over time are the most important for different emotions. The current structure, which has many complex parts, takes too much computing power. Real-time emotion recognition is important for emotional brain-computer interfaces (BCIs), monitoring of mental health, and interaction between humans and robots. This model can be possible by customizing architecture and using edge computing. Checking integration with additional indications, such as facial electromyography (EMG) or eye-tracking, can achieve a more flexible and accurate emotional recognition system. The challenge must create a merger mechanism that works with all different types of data and time solutions that are each model. The CDA-GAF framework shows that a hybrid function carefully integrates graph-based spatial attention, temporary attention, and domain optimization, forming an extraordinarily effective strategy to address the complicated EEG-based feelings. Not only does it work better than anything else, but it also sets a strong base to create loving computer systems that are more useful and can be used under several conditions.

References

[1] T. Li, Z. Wang, H. Liu (2025). Adversarial Domain Adaptation-Based EEG Emotion Transfer Recognition. IEEE Access, IEEE, 32706 – 32723. [DOI]

[2] Y. Yang, Z. Wang, Y. Song, Z. Jia, B. Wang, T.P. Jung, F. Wan (2025). Exploiting the Intrinsic Neighborhood Semantic Structure for Domain Adaptation in EEG-based Emotion Recognition. IEEE Transactions on Affective Computing, IEEE, 1-3. [DOI]

[3] C. Gao, L. Jia, J. Xu, P. Yang (2025). UMDA-DDSTGN: An Unsupervised Meta-Domain Adaptation Method Using Dynamic Directed Spatial-Temporal Graph Network for EEG-based emotion recognition. Knowledge-Based Systems, 325, 113938. [DOI]

[4] X.C. Zhong, Q. Wang, R. Li, Y. Liu, S. Duan, R. Yang, J. Sun (2025). Unsupervised Domain Adaptation with Pseudo-Label Propagation for Cross-Domain EEG Emotion Recognition. IEEE Transactions on Instrumentation and Measurement, IEEE. [DOI]

[5] Z. Lyu, Z. Zuo, C. Chen, Y. Fang (2025). Mutual Information Disentanglement Based Domain Adaptation Model for EEG Emotion Recognition. IEEE Signal Processing Letters. [DOI]

[6] C. Ahuja, D. Sethia (2025). Transit-eeg—a framework for cross-subject classification with subject specific adaptation. IEEE Transactions on Cognitive and Developmental Systems, IEEE, 17(4), 923-937. [DOI]

[7] L. Hu, C. Tan, Y. Tian (2025). Adaptive dual-graph learning joint feature selection for EEG emotion recognition. Journal of King Saud University Computer and Information Sciences, 37(4), 69. [DOI]

[8] W. Tan, H. Zhang, Y. Wang, W. Wen, L. Chen, H. Li, N. Zeng (2025). SEDA-EEG: A semi-supervised emotion recognition network with domain adaptation for cross-subject EEG analysis. Neurocomputing, 622, 129315. [DOI]

[9] M. Hilali, A. Ezzati, S. Ben Alla (2025). CMHFE-DAN: A Transformer-Based Feature Extractor with Domain Adaptation for EEG-Based Emotion Recognition. Information, 16(7), 560. [DOI]

[10] X. Ju, X. Wu, S. Dai, M. Li, D. Hu (2025). Domain adversarial learning with multiple adversarial tasks for EEG emotion recognition. Expert Systems with Applications, 266, 126028. [DOI]

[11] X. Deng, X. Hong, L. Ai, X. Li, C. Li (2025). Multi-Source Reinforced Selective Domain Adaptation for Cross-Subject and Cross-Session EEG-Based Emotion Recognition. IEEE Access, IEEE, [DOI]

[12] Q. Zhu, T. Zhu, L. Fei, C. Zheng, W. Shao, D. Zhang, D. Zhang (2025). Multi-Modal Cross-Subject Emotion Feature Alignment and Recognition with EEG and Eye Movements. IEEE Transactions on Affective Computing, IEEE, 1-15. [DOI]

[13] Y. Zhang, Z.S. Chen (2025). Harnessing electroencephalography connectomes for cognitive and clinical neuroscience. Nature Biomedical Engineering, 1-16. [DOI]

[14] H. Song, Q. She, F. Fang, S. Liu, Y. Chen, Y. Zhang (2025). Domain generalization through latent distribution exploration for motor imagery EEG classification. Neurocomputing, 614, 128889. [DOI]

[15] J. Shen, L. You, Y. Ma, Z. Zhao, H. Liang, Y. Zhang, B. Hu (2025). UA-DAAN: An Uncertainty-aware Dynamic Adversarial Adaptation Network for EEG-based Depression Recognition. IEEE Transactions on Affective Computing,IEEE, 1-12. [DOI]

[16] Z. Xiao, Q. She, F. Fang, M. Meng, Y. Zhang (2025). Auxiliary classifier adversarial networks with maximum subdomain discrepancy for EEG-based emotion recognition. Medical & Biological Engineering & Computing, 1-15. [DOI]

[17] C. Xu, Y. Song, Q. Zheng, Q. Wang, P.A. Heng (2025). Unsupervised multi-source domain adaptation via contrastive learning for eeg classification. Expert Systems with Applications, 261, 125452. [DOI]

[18] G. Ghous, S. Najam, M. Alshehri, A. Alshahrani, Y. AlQahtani, A. Jalal, H. Liu (2025). Attention-Driven Emotion Recognition in EEG: A Transformer-Based Approach with Cross-Dataset Fine-Tuning. IEEE Access, IEEE, 69369-69394. [DOI]

[19] H. Liu, X. Jin, D. Liu, W. Kong, J. Tang, Y. Peng (2025). Joint disentangled representation and domain adversarial training for EEG-based cross-session biometric recognition in single-task protocols. Cognitive Neurodynamics, 19(1), 31. [DOI]

[20] H. Feng, S. Wang, H. Lv, C. Nie, W. Feng, H. Peng, Y. Zhao (2026). Cross-subject seizure detection with vision transformer and unsupervised domain adaptation. Biomedical Signal Processing and Control, 111, 108341. [DOI]

[21] Y. Liu, L. Qin, X. Chen, R.L.B. Jeannes, J.L. Coatrieux, H. Shu (2025). Advancing Cross-Subject Domain Generalization in Brain-Computer Interfaces with Multi-Adversarial

Strategies. IEEE Transactions on Instrumentation and Measurement, IEEE, 74. [DOI]

[22] N. Zhou, L. Jika, W. Wang, Y. Xie, Y. Du, Y.C. Soh (2025). BERN: A Novel Framework for Enhanced Emotion Recognition through the Integration of EEG and Eye Movement Features. IEEE Transactions on Cognitive and Developmental Systems, IEEE, 1-3. [DOI]

[23] A. Abgeena, S. Garg, N. Goyal, and J. R. PC (2025). NeuroEmo: A neuroimaging-based fMRI dataset to extract temporal affective brain dynamics for Indian movie video clips stimuli using dynamic functional connectivity approach with graph convolution neural network (DFC-GCNN). Computers in Biology and Medicine, 194, 110439. [DOI]

[24] M. Raparthi, N.R. Mitta, V.K. Dunka, S. Gudekota, S.P. Pattyam, V.S.P. Nimmagadda (2025). Deep learning model for patient emotion recognition using EEG-tNIRS data. Neuroscience Informatics, 100219. [DOI]

[25] C.A.U. Hassan, M. Ehatisham-ul-Haq, F. Murtaza, A.U. Yasin, S.S. Ullah (2025). EmoTrans attention based emotion recognition using EEG signals and facial analysis with expert validation. Scientific Reports, 15(1), 22004. [DOI]

Funding

No funding was received for the conduct of this research

Conflict of interest

The authors declare that no conflict of interest exists.

Does the Article Screened for Similarity?

Yes.

About the License