Proceedings of CONF-MLA 2026 Symposium: Intelligent Systems and Automation: AI Models, IoT, and Robotic Algorithms
DOI: 10.54254/2755-2721/2026.LD38193

A Survey on Attention-Based Deep Learning Methods for EEG Emotion Recognition

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Abstract. Electroencephalography (EEG)-based emotion recognition has attracted increasing attention in recent years because of its potential applications in brain-computer interfaces, intelligent healthcare, and affective computing. With the rapid development of deep learning, attention mechanisms have gradually become an important component of EEG emotion recognition models, since they are able to improve feature representation by focusing on more informative EEG signals. This paper reviews recent attention-based deep learning methods for EEG emotion recognition, with particular attention to channel attention, temporal attention, and self-attention implemented in Transformer-based architectures. Their main ideas, representative models, as well as their advantages and limitations are discussed and compared. This paper finds that although existing studies have achieved encouraging performance, several challenges, including cross-subject variability, limited EEG datasets, and insufficient model interpretability, still remain. Future research is expected to develop more efficient and interpretable attention mechanisms while exploring larger datasets and multimodal learning frameworks, which may further improve the robustness and practical application of EEG emotion recognition systems.

Keywords: Electroencephalography, Emotion Recognition, Attention Mechanism, Deep Learning

1. Introduction

Emotion recognition is an important topic in affective computing. It supports applications such as brain–computer interfaces (BCIs), intelligent healthcare, and human–computer interaction (HCI). Among various physiological signals, research in the area of Electroencephalography (EEG) has attracted extensive scholarly attention because it has been widely used to directly reflect brain activity and provides relatively objective information about human emotional states [1].

Early EEG emotion recognition mainly relied on handcrafted feature extraction and traditional machine learning algorithms. With the rapid development of deep learning algorithms, data-driven models, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), graph neural networks (GNNs), and Transformer-based architectures, have achieved significant improvements in emotion classification by automatically learning feature representations from EEG signals [2].

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Attention mechanisms have become an important component of EEG emotion recognition models in recent years. By assigning different weights to EEG channels, temporal information, or feature representations, attention-based models are able to capture more discriminative information than conventional methods. Although numerous studies have already proposed new attention-based architectures, systematic comparisons of different attention strategies and their characteristics are still limited [1, 2].

This paper surveys attention-based deep learning methods for EEG emotion recognition and includes a comparative experimental analysis. It groups existing studies by attention mechanism and network architecture, then compares representative methods using publicly available EEG datasets. The paper also discusses current challenges and possible directions for later work.

The aim is more limited than offering a complete account of the field. Instead, it provides an organized overview of how attention has been used in EEG emotion recognition and what differences appear across model designs and datasets. In that sense, it may serve as a reference point for future studies on attention-based EEG emotion recognition and for work on more practical and reliable EEG-based intelligent systems.

2. Background of EEG emotion recognition

2.1. EEG signals and emotion recognition

EEG records the electrical activity of the brain through electrodes placed on the scalp. It has been widely used to investigate cognitive and emotional processes. Compared with external behavioral signals, such as facial expressions and speech, EEG provides more direct information about neural activity and is less influenced by intentional expression, making it a useful modality for emotion recognition [1, 3]. In many EEG emotion recognition studies, emotions are represented using the two-dimensional valence–arousal model, where valence describes the degree of pleasantness and arousal reflects the intensity of emotional activation. This representation is widely used in benchmark datasets such as DEAP and provides a common basis for emotion classification experiments [3].

2.2. Deep learning in EEG emotion recognition

Deep learning has improved EEG emotion recognition by learning features automatically from raw or minimally processed EEG signals. CNNs are effective at extracting local spatial features, and compact architectures such as EEGNet have demonstrated that lightweight convolutional networks can achieve competitive performance on EEG-related tasks [2, 4]. In recent years, GNNs have been used to model relationships among EEG channels, and Transformer-based architectures have shown that they can learn long-range contextual information well. Even with these advances, identifying the most informative features is still difficult. Consequently, attention mechanisms have become an increasingly important component of modern EEG emotion recognition models [2, 5].

3. Attention-based deep learning methods

As deep learning is evolving, the attention mechanism is becoming a hot topic in EEG emotion recognition. They make models pay attention to the parts of EEG signals containing useful information instead of treating every feature equally. In recent years, numerous attention schemes have been proposed by researchers. Though all these attention schemes aim to enrich the feature

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representation, they emphasize different information and built in the neural network architecture in different ways. Most existing methods fall into three categories: channel attention, time attention and attention-based on the self-attention scheme. Every kind of attention tries to emphasize different part of EEG feature learning and has both advantages and disadvantages [2].

3.1. Channel attention

Channel attention assigns different weights to EEG channels according to how much each EEG channel contributes to emotion recognition. Emotional activity refers to different brain regions. Giving every EEG channel the same attention therefore introduces redundant information and degrades classification performance. Channel attention helps the model pay more attention to informative EEG channels and suppress less informative channels, which leads to informative features [2, 5].

Traditional channel selection techniques require that channels be deleted before training according to certain criteria. Channel attention, however, works a bit differently. Instead of fixing the channel set beforehand, the model can learn the importance of each EEG channel through optimization. That is, the model has more freedom, because the channel weight can vary for different subjects and even different emotions, but still maintain information from the channels that are less dominant but are still useful. That is why the studies recently approached manual channel selection by gradually shifting to adaptable channel weighting strategies [2, 6].

Recently, researchers have added channel attention to deep learning models for EEG emotion recognition. Instead of choosing important electrodes by hand, channel attention modules learn channel weights during training. The selection step has been built in the model.

Researchers have used this approach in CNN-based and Transformer-based models, often in addition to spatial feature extraction, to improve the performance of the classification. For example, in the MECAM model, a multi-axis channel attention mechanism is adopted to extract complementary information from different EEG channels, and performs better than baselines on benchmark data [6].

Channel attention is useful, but it still has some limits. Many existing works use channel attention to improve the accuracy of a classifier, and the learned attention weights may not be easily explained in neurophysiological terms. There is also a dataset issue. Different datasets use different channel types, so channel attention models do not work well across datasets and subjects [2].

3.2. Temporal attention

Temporal attention model gives different weights to the EEG time steps; the model pays more attention to the parts of the signal that contain useful information. An emotional response changes through time, so some EEG segments contain information important to emotion recognition, and those of them are more important for emotion recognition than the others. Standard sequential models treat temporal information more evenly, but temporal attention enables models to focus on cues related to emotion and downweight those temporal signals not very relevant [2]. Unlike channel attention, temporal attention concerns how EEG signals evolve over time and the order of change of the signals, rather than the distribution of EEG signals over channels. Emotional responses happen over time instead of at a certain instant; therefore, there are segments of data that are more suitable for encoding emotion information than others. For this reason, temporal attention could also be coupled with convolutional or recurrent structures to do local feature extraction and learning of temporal dependency at the same time [2, 7].

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There are some recent works introducing temporal attention to deep learning models to help to better learn how EEG signals represent information. For instance, some works integrated temporal attention with convolutional network and Transformer architectures, so that the model can learn both short-term temporal features as well as longer temporal contextual information. For several public EEG emotion recognition datasets, they achieved better accuracy with such approaches. This shows the power of temporal attention to help to model the changing nature of emotions in EEG [7].

However, temporal attention alone might be ignorant of the relationships among different EEG channels. Hence, recent studies seek to integrate temporal attention with self-attention and Transformers to capture more interpretable feature learning, and we discuss this in the following section [4].

3.3. Self-attention and transformer-based methods

Self-attention is now common for EEG emotion recognition, because it enables models to learn relationships among the different EEG representations without relying on recurrent structures. Channel attention and temporal attention usually each deal with only one slice of the input, whereas self-attention deals with interactions over all the input tokens at the same time. The difference makes a difference. It facilitates modelling long-range contextual information more effectively, especially when EEG signals have long temporal dependencies that conventional neural networks tend not to model well [2, 5].

Unlike traditional attention, self-attention combines spatial information and temporal information neither in a clear way. It builds the global relation between all input representations; thus, different EEG features are able to interact, even if they occur at different positions in the sequence. This also boosts parallel computation during training and makes Transformer-based models better to be applied to long EEG sequences where recurrent networks may have troubles with capturing long-range dependencies [2, 5].

Transformer-based architectures extend self-attention by combining multi-head attention and feed-forward networks in one model. For instance, EmT first transforms EEG signals into a sequence of temporal graphs, then extracts the graph representation, and finally learns the temporal context using a Transformer encoder. Compared with many traditional deep models, this model can model the long-range dependency of time while maintaining the spatial relationship between the EEG channels. For this reason, it is suitable to deal with cross-subject emotion recognition [5].

Transformer-based methods perform well, but they still have some clear limitations. Transformers' computational cost is usually higher than that of traditional deep learning methods, and they often require relatively large training samples before their performance reaches a stable point. Self-attention provides the model a flexible way to learn features; however, the attention weights output by the model are not always straightforward to explain in neurophysiological terms. A recent trend is the integration of graph representations, temporal modelling and attention mechanisms within one framework. The direction towards the hybridization of models is also a useful trend for future EEG emotion recognition research [5]. Therefore, improving both computational efficiency and model interpretability is likely to remain an important research direction in future EEG emotion recognition studies.

4. Discussion and future directions

Recent studies have shown that attention mechanisms have become an important part of EEG emotion recognition models because they allow different types of information to be learned more

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effectively. Earlier sections showed that channel attention is mainly used to pick out informative EEG channels, while temporal attention helps the model track how emotional responses change over time. Transformer-based methods use self-attention to learn long-range dependencies that conventional neural networks often miss. Even so, the reported results on public datasets do not remove all of the main problems.

The clearest unresolved issue is cross-subject generalization. EEG signals differ a lot from one person to another, so a model trained on one group may lose accuracy when it is tested on unseen subjects. Data availability is another constraint. Public EEG emotion datasets are still fairly limited, and this seems to matter especially for Transformer-based models, which usually need more training data to perform well. Attention mechanisms also improve feature learning at the cost of interpretability in some cases. Higher attention weights can be identified, but it is still hard to explain why particular channels or temporal segments are emphasized, and that makes practical use less straightforward.

Future work could focus more directly on lightweight model design, multimodal learning, and self-supervised learning. Better interpretability also matters. More interpretable attention mechanisms and larger EEG datasets may improve both performance and practical usability.

5. Conclusion

This paper reviewed recent advances in attention-based deep learning methods for EEG emotion recognition. First, the background of EEG emotion recognition and the development of deep learning methods were introduced. Then, this review discussed representative attention mechanisms from several angles, including channel attention, temporal attention, and self-attention. These methods have improved how deep learning models learn informative EEG representations, but their advantages and limits differ across application scenarios. Overall, attention mechanisms have become a major direction in EEG emotion recognition research, and recent studies suggest better recognition performance with these methods. Some problems still remain. Cross-subject variability, limited training data, and model interpretability continue to affect results. Because this review had a limited scope, some newer attention mechanisms, including spatial and frequency attention, were mentioned only briefly instead of being examined in detail. These areas need more study. Future work may benefit from combining more efficient attention mechanisms with larger datasets and multimodal information to support the practical use of EEG emotion recognition in areas such as brain–computer interfaces and intelligent healthcare.

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