Multi-View Deep Clustering for Depression Subtype Identification Across Multi-Band EEG Topographies

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Abstract. The significant heterogeneity of Major Depressive Disorder (MDD) necessitates objective subtyping that transcends traditional symptomatology. With the development of machine learning algorithms, using machine learning to identify potential biomarkers has emerged as an efficient approach. However, existing machine learning-based studies on depression are mostly limited to simple binary classification or rely on pre-set features. This study validates a novel unsupervised framework, integrating a CNN-Transformer with the DEMVC model, to identify depression subtypes from resting-state EEG topographies across different frequency bands. The results show that the fusion of multi-band significantly superior to single-band approaches in clustering stability and subtype separability. Specifically, the Alpha-Beta-Theta combination emerged as the best band combination. Ablation studies further revealed the distinct roles of the frequency bands: the Theta band captures core depressive pathology, whereas the Alpha band may be better considered as an indicator of 'near-healthy status' rather than a mere disease marker. This study innovatively takes multi-bands as multi-view inputs for multi-view deep clustering, resolving the challenge of classifying depression subtypes and providing a robust and explicable new paradigm for this task.

Keywords: Multi-view Deep clustering, Depression subtypes, EEG Topographic.

1. Introduction

Major Depressive Disorder (MDD) presents significant difficulties for conventional symptom-based clinical diagnosis and treatment due to its heterogeneity. To elucidate the potential neurobiological difference across individuals, precise subtype classification based on objective biomarkers has become an imperative issue. Electroencephalography (EEG), characterized by its non-invasiveness and low burden, has emerged as an ideal tool for solving this issue [1].

Compared with healthy controls, depression patients reveal marked contrast in resting-state EEG, particularly within the Alpha, Beta, and Theta bands, whereas less obvious differences are observed in Delta and Gamma bands [2]. However, the lack of consensus regarding the specific patterns of these changes poses a significant problem. A compelling explanation is that depression is not a single disease type but comprises multiple subtypes with distinct neurophysiological characteristics. Consequently, mixing all patients into a homogeneous group may mask specific signal patterns. Furthermore, emerging evidence suggests that the interaction between frequency bands may be more informative than an isolated band. Li et al. demonstrated a significant correlation between depressive states in healthy individuals and the Theta-Beta power ratio, revealing the necessity of multi-band analysis [3].

In recent years, EEG analysis based on machine learning has shown great results in identifying depression. Researchers have achieved classification accuracy as high as 93.14% by using a CNN-Transformer model on low-channel EEG data [4], and 96.27% by processing EEG signals into multi-band topographies with MCTNet [5]. However, the focus has largely been on distinguishing patients from healthy individuals, rather than identifying different subtypes, which is more vital for treatment. While some studies, such as Zhou et al.'s work on frontal Alpha asymmetry, have successfully categorized MDD patients, they usually rely on pre-set features. This approach limits their ability to discover new, unknown subtypes [1][6-8].

Deep clustering extracts distinctive representations from unlabeled data, leading to more robust and efficient unsupervised clustering [9]. Multi-view deep clustering, in particular, can treat EEG

features from different frequency bands as "views," capturing both the consistency and complementary information shared across them. Given the success of the DEMVC model in handling multi-view data [10], this study redesigned a new autoencoder based on CNN-Transformer architecture to replace the original one.

This research used EEG topographies from different frequency bands (Delta, Theta, Alpha, Beta, Gamma) as multi-view inputs to build an improved multi-view clustering framework. The core objective was to systematically compare various band combinations to determine which generates the most stable and interpretable clustering results. This process also served to verify that multi-view fusion plays an effective role in resolving the classification issue of depression subtypes. Additionally, through ablation studies, this study analyzes the specific contributions of different bands(especially Alpha and Theta) to subtype classification and proposes a reasonable assumption about the considerable inconsistencies between previous studies in the alpha band. These findings provide a more objective and accurate method of classifying depression subtypes.

2. Method

This study developed a framework for identifying depression subtypes based on multi-view deep clustering. In this framework, EEG features from various frequency bands are treated as different "views." This allows the model to effectively mine information from each view, resulting in more accurate clustering for unlabeled data.

2.1. Dataset and Multi-view Data Construction

The dataset for this study consists of 200 participants, including 150 patients diagnosed with depression and 50 healthy controls. The data comprises resting-state EEG topographies covering five key frequency bands: Delta (δ), Theta (θ), Alpha (α), Beta (β), and Gamma (γ). Figure 1 displays the EEG topographies of two randomly selected samples to visualize the variations in brain activity patterns across these frequency bands.

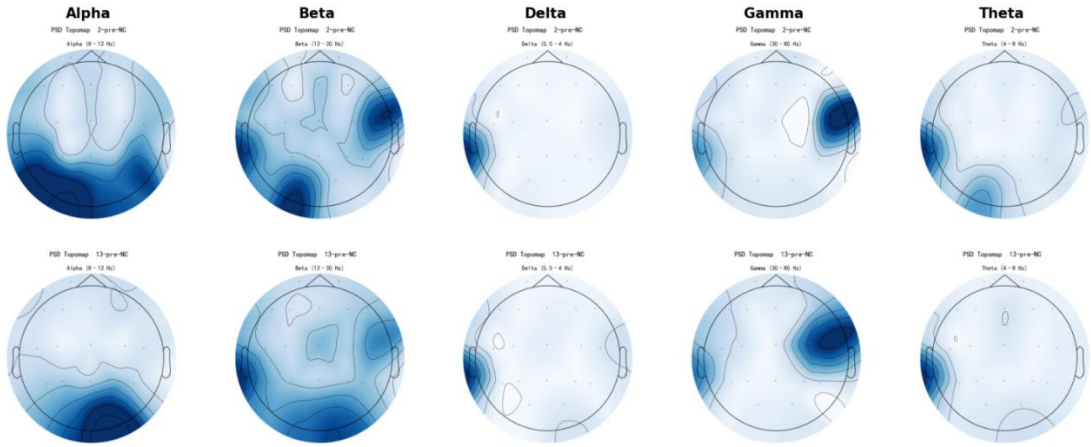

Fig. 1 EEG topographies across five frequency bands (Picture credit: Original)

To explain how fusing different frequency bands improves depression subtypes classification. This study treated various band combinations as multi-view samples and processed them using an advanced Deep Embedded Multi-view Clustering (DEMVC) model. Based on findings from neuroscience and clinical research[3,6,8], seven representative combinations were defined: five dual-band (Alpha-Beta, Alpha-Theta, Alpha-Delta, Alpha-Gamma, Beta-Theta), one tri-band (Alpha-Beta-Theta), and one comprehensive all-band set. Additionally, to verify the necessity of multi-band

fusion, this study also conducted ablation studies using a single-view IDEC model, with the Alpha, Beta and Theta bands serving as independent inputs for comparison [9].

All experiments in the same band combination shared the same pre-trained parameters. Each experimental run was repeated to ensure the results were stable and reliable.

2.2. Model Enhancements

The framework of this study is primarily based on DEMVC [10], which effectively trains multiple-view autoencoders using a collaborative learning strategy. However, simple CNN encoders are often insufficient for capturing the complex spatial features of EEG topographies. Given Yu et al.'s success with CNN-Transformer models for depression identification [4], this study replaced the original encoder and decoder with a weight-sharing CNN-Transformer network to serve as a more suitable autoencoder.

2.3. Early-Stopping

To prevent performance degradation during the training process, this study employs the collaborative Early-Stopping mechanism introduced in DEMVC [10]. This strategy helps ensure greater model stability and more robust clustering outcomes.

The collaborative Early-Stopping mechanism monitors the clustering assignments from different views for the same sample throughout the training process to determine the optimal stopping point. During iteration, the model tracks agreement between different views. Once the differences in assignments between views fall below a preset threshold, which means clustering results stabilize for most samples, the training process stops automatically. This approach helps avoid overfitting from over-training and prevents the formation of false or meaningless clusters. This mechanism ensures the validity and robustness of the results while improving the efficiency of the multi-view clustering task.

2.4. Evaluation Metrics

Since the clustering task in this study is unsupervised and lacks external objective labels, this study employed two widely used internal evaluation metrics to assess clustering performance objectively and quantitatively: the Silhouette Coefficient and the Davies-Bouldin Index (DBI). These metrics assess clustering quality from different angles, ensuring a thorough and balanced evaluation of the model.

The Silhouette Coefficient assesses the similarity between an object and its own cluster compared to other clusters. For an individual sample $s(i)$, it is given by:

$$s(i) = \frac{b(i)-a(i)}{\max\{a(i),b(i)\}} \tag{1}$$

In this formula, $a(i)$ is the average distance to other samples in the same cluster, and $b(i)$ is the smallest average distance to samples in a different cluster. The metric ranges from $-1\ to\ 1$, where values close to 1 indicate well-defined clusters. Values near -1 imply incorrect assignment.

The Davies-Bouldin Index (DBI) measures the average similarity between each cluster and its most similar neighbor. It is computed as:

$$DBI = \frac{1}{k}\sum_{i=1}^{k} max_{j\neq i}\left(\frac{s_i+s_j}{d_{ij}}\right) \tag{2}$$

where k is the cluster count, s_i is the average distance of samples in cluster i to their center, and d_{ij} is the distance between the center of clusters i and j. A lower DBI value indicates that clusters are more compact and better separated, signifying better clustering performance.

3. Results and Discussion

To explore the biological implications of the depression subtypes, this study introduced a key quantitative metric: Healthy Control Rate (HCR). The metric evaluates the similarity between a subtype and a healthy state by calculating the proportion of healthy control samples in each cluster. Given the baseline healthy ratio of 25% in the dataset, the value of HCR reflects the severity level in each subtype. Specifically, an HCR significantly below the baseline suggests severe pathological features, while a higher HCR indicates a state close to healthy controls.

3.1. Same band combinatio

To verify the feasibility and stability of the model in identifying depression subtypes, the study analyzed training convergence and consistency using the same band combination input. (Take the Alpha-Beta combination as an example).

Figure 2 shows the curve of clustering performance internal metrics changing with the iterations in a single experiment. As training iterations increase, the Silhouette Coefficient rises steadily to 1, while the Davies-Bouldin Index (DBI) drops to 0. This trend indicates the effectiveness of the model for the classification task of depression subtypes. It maps EEG topographies features into a compact low-dimensional space successfully, confirming the feasibility of subtype classification.

Additionally, the study had a further discussion in the stability of results across multiple independent experiments using the same frequency band combination. Figure 3 presents a map of the ARI for five randomly selected experiments to compare the similarity in each test. The ARI values remain at a high level (ranging primarily from 0.73 to 0.84), verifying the model has the ability of converging to a similar clustering result with the different initial parameters. The reproducibility of the results proves that the model captures the potential pathological features in the EEG topographies rather than random noise. It indicates the robustness of the clustering model and provides reliable evidence for the feasibility of using deep clustering methods to solve the problem of depression classification.

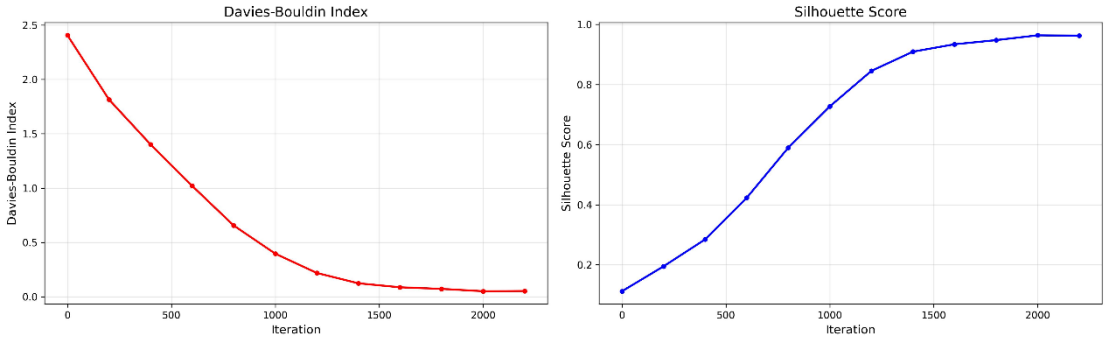

Fig. 2 Changes in internal metrics over iterations (Left: Davies-Bouldin Index; Right: Silhouette Coefficient) (Picture credit: Original)

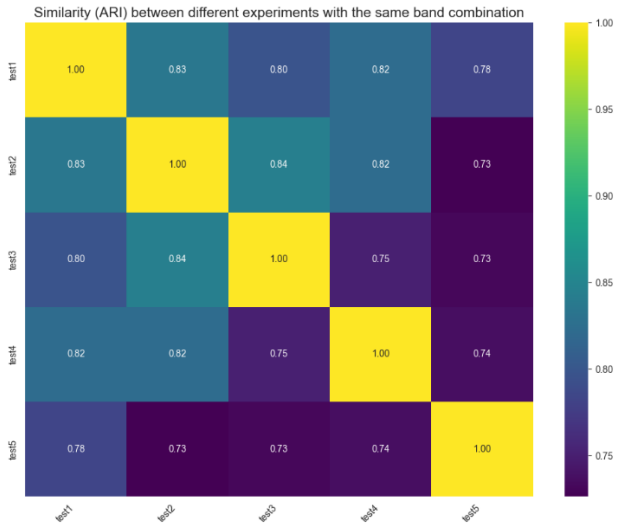

Fig. 3 Similarity (ARI) between different experiments with the same band combination (Picture credit: Original)

3.2. Different band combination

With the exception of the full-band combination, all band combinations demonstrated clear clustering boundaries. To enhance the stability of clustering results, this study introduced a filtering trick that calculates the probability of a sample consistently belonging to a specific subtype. Then, set a probability threshold to filter out those who are below this value. Using this mechanism, the results eliminate ambiguous samples with an uncertain assignment, leaving only core samples that have distinct features. Based on this strategy, the study compared the difference between 0.8 and 0.9 thresholds on the Healthy Control Rate (HCR) distribution. Figure 4a shows the HCR distribution with a threshold of 0.8, in contrast to a threshold of 0.9 used in Figure 4b.

The higher threshold aimed to select the most representative pathological features by ignoring unstable samples. It may be a perfect choice to analyze the typical features of different subtypes. However, the strict standard can lead to extreme sample distributions and the loss of clinical significance. For instance, the Alpha-Delta band combination showed a minimum HCR of 0 at the 0.9 threshold. On the other hand, a lower threshold introduces some uncertain samples and reduces the distinctions between subtypes, but it contains ambiguous samples that reflected the real clinical complexity and the continuity of disease. Since the 0.8 threshold provides a more generalized sample while maintaining acceptable stability, it was selected for further analysis.

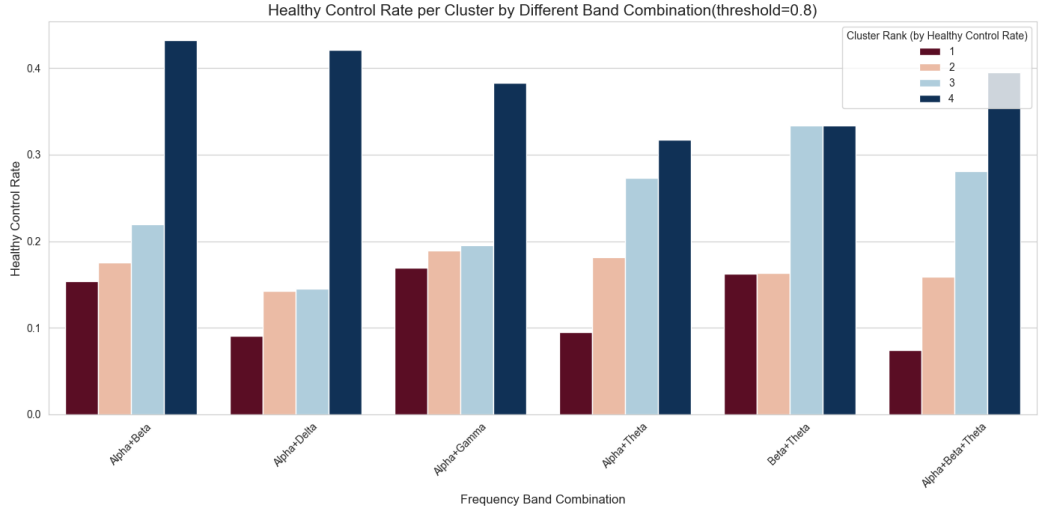

Fig. 4a Comparison of HCR across different frequency bands under different threshold settings (threshold = 0.8) (Picture credit: Original)

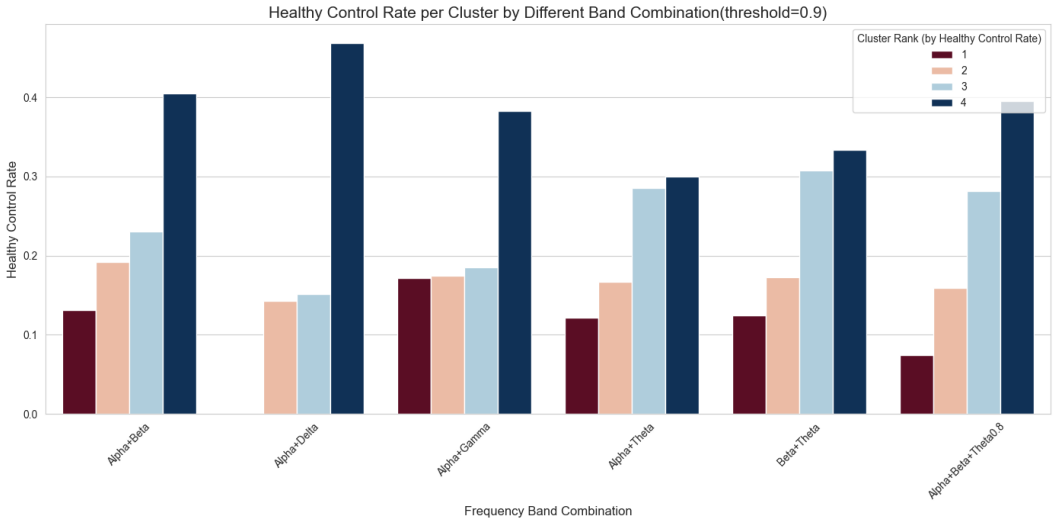

Fig. 4b Comparison of HCR across different frequency bands under different threshold settings (threshold = 0.9) (Picture credit: Original)

3.3. Discussion

Analysis of the HCR for clustering results across different frequency band combinations reveals that different combinations uncover different subtype structures.

3.3.1 Alpha-Beta-Theta band

A comparison of clustering results across different frequency band combinations reveals that the Alpha-Beta, Alpha-Theta, and Alpha-Beta-Theta combinations all clearly divide samples into four subtypes with distinct boundaries. This finding is highly consistent with the review by Miljevic et al., which concluded that EEG differences between patients and healthy controls are primarily concentrated in the Alpha, Beta, and Theta bands, whereas differences in the Delta and Gamma bands are often insignificant or lack of consistency [2].

Furthermore, the smooth progressive change in HCR, especially in Alpha-Beta-Theta band combination, which shows an increase from 0.077 (Cluster 1) to 0.421 (Cluster 4), indicates the combination of different bands not only effectively distinguishes subtypes but also uncovers a continuous pathological variation ranging from "typical severe depression" to a "near-healthy state." This provides a strong evidence for classification of depression. A further ablation study with single-band inputs was conducted to reveal the specific contribution of each frequency band to subtype classification (Table 1 and Figure 5).

Table 1. HCR of each cluster under different frequency band combinations

	Alpha	Beta	Theta	Alpha-Beta	Alpha-Theta	Beta-Theta	Alpha-Beta-Theta
Cluster1	0.173	0.214	0.105	0.158	0.098	0.167	0.077
Cluster2	0.186	0.227	0.156	0.179	0.186	0.167	0.163
Cluster3	0.227	0.308	0.319	0.225	0.281	0.343	0.290
Cluster4	0.420	0.308	0.326	0.455	0.342	0.368	0.421

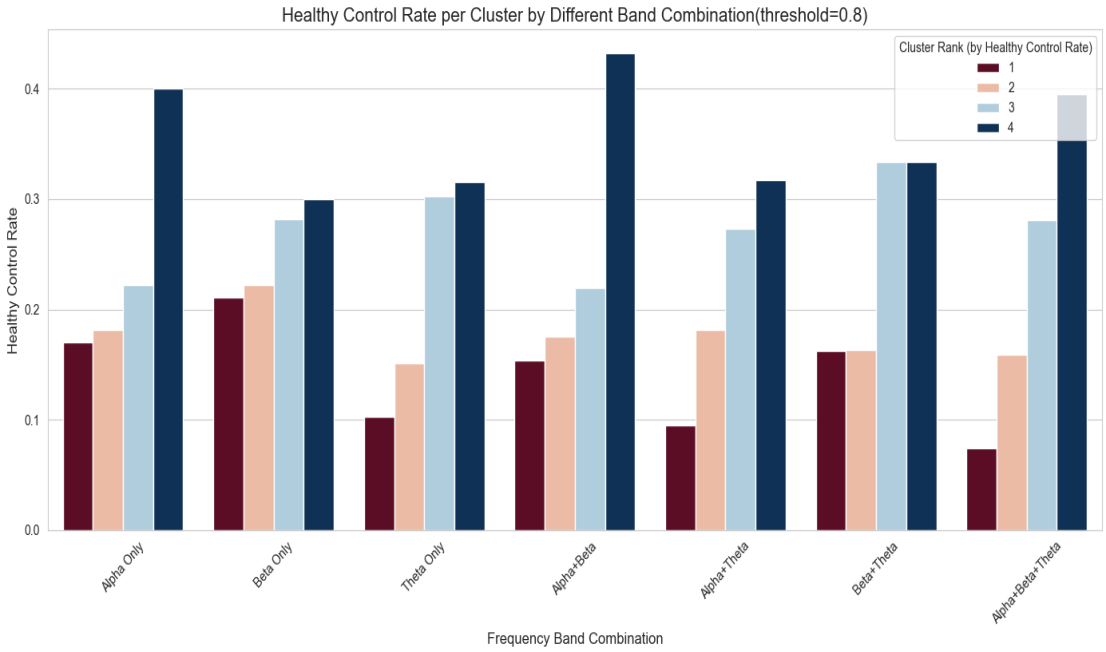

Fig. 5 Ablation study: HCR distribution under different frequency band combinations. (Picture credit: Original)

The results indicate that the Alpha band has a more effective capabilities in detecting high-HCR (near-healthy state) subtypes. With Alpha input alone, Cluster 4 achieved an HCR of 0.420, significantly higher than the Theta band's peak of 0.326. In contrast, the Theta band proved more effective at distinguishing low-HCR (typical depression) subtypes. In the Theta-only result, Cluster 1 had an HCR as low as 0.105, with an inclination to a lower HCR. Using the Beta band alone resulted in a concentrated HCR distribution across clusters (0.214 - 0.308) , which demonstrates only use Beta band can not distinguish depression subtypes. However, combining Beta with Alpha (Alpha-Beta combination) produced a significant multi-view effect: this combination not only maintained clear distinctions in classification but also identified the highest HCR among all combinations (Cluster 4, HCR = 0.455). Similar results were reported by Zhou et al. using Alpha-Beta combinations [6].

From a comprehensive perspective, the Alpha-Beta-Theta combination delivers the best performance. Although its highest HCR (0.421) was slightly lower than that of the Alpha-Beta combination, it had captured severe depression features (Cluster 1 HCR = 0.077, the lowest recorded). This leads to the widest range and the most distinctive progressive variation in HCR. This confirms that fusing EEG topographies of different band successfully combines Alpha's sensitivity to near-healthy states, Theta's specificity for typical depressive features, and Beta's supportive role, outperforming single bands in the result of subtype classification.

3.3.2 Other Band

Although the Beta-Theta combination failed to effectively distinguish four clear subtype categories, it exhibited a distinct bipolar distribution. The four clusters in this combination were clearly divided into two levels: Clusters 1 and 2 had very low HCRs, while Clusters 3 and 4 remained at higher results. This suggests Beta-Theta combination may be more suitable to determine whether a person is suffering from depression. And the result seems to support the viewpoint the Beta-Theta ratio is related to the depressive state [3], since Beta-Theta combination was more like distinguishing the depressive state rather than conducting subtype classification. In contrast, introducing the Gamma and Delta bands did not significantly improve subtype classification and even underperformed compared to the Alpha band alone, reflecting the Gamma and Delta bands have very little effect on the classification of depression subtypes.

3.3.3 Future Directions

In summary, various frequency band combinations with multi-views deep clustering model can solve the problem of classification of depression subtypes, to a certain extent. And the combination of Alpha-Beta-Theta offers the most interpretable and clearest progressive subtype results. Previous research indicates that studies based on single frequency bands often fail to reach a consensus on the direction of functional connectivity changes, leading to different explanations. This study demonstrates that different frequency bands carry complementary neurophysiological information. The Alpha-Beta-Theta combination not only outperforms single bands but also effectively reveals a clear variation from near-healthy to typical depression. Therefore, this combination is considered as the best combination for depression subtype classification in this study.

The results of the ablation study also provide a new perspective for depression research. While Alpha band has become a common target for diagnostic investigation, its results are often uncertain. This study shows that Alpha is actually more sensitive to "near-healthy" subtypes, which might reflect an inclination to a healthy state. Meanwhile, the Theta band shows a strong capability of distinguishing low-HCR samples, serving as a better indicator of core pathology. These results suggest future studies should treat Alpha as a measure of "near healthiness" or "recovery effect" rather than just a marker of disease.

However, there are still significant limitations. First, as the study relied primarily on objective metrics (e.g., HCR), it lacks a corresponding analysis of clinical symptom scales (e.g., HAMD factor scores) for each subtype. Future research needs to combine clinical data to verify whether the results of the subtypes distinguished by multi-view deep clustering show significant differences in clinical indicators. Additionally, this study employed a filtering mechanism (threshold = 0.8) to obtain stable clustering results for further discussion. This effectively improved the stability of the results, while the excluded samples may represent the common atypical or mixed-type cases in clinical practice. These ambiguous samples often possess significant clinical research value. Future studies could consider employing fuzzy clustering or soft classification to explore these transitional states, aiming to construct a more continuous and explicable diagnostic model for the classification of depression subtypes.

4. Conclusion

This study innovatively replaces the simple CNN autoencoder in the DEMVC framework with a CNN-Transformer architecture, achieving efficient feature fusion for multi-band EEG topographies. The results demonstrate that, compared to single-band input, the multi-view fusion strategy more effectively captures the complex pathological features of depression. In particular, the Alpha-Beta-Theta combination delivered the best performance. Ablation studies further revealed a complementary mechanism: the Alpha band seems to identify healthy-like subtypes, whereas the Theta band targets typical depressive state. Future research should focus on the neurophysiological interpretation of core subtypes and integrate clinical data for validation, aiming to translate clustering results into practical clinical diagnostic tools.

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