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MRI Data-Based Major Depressive Disorder Classification Using Static and Dynamic Functional Connectivity with Support Vector Machines

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Abstract: Major Depressive Disorder (MDD) is a widespread psychiatric condition that significantly affects emotional regulation, cognition, and overall quality of life. Traditional diagnostic approaches rely heavily on subjective clinical assessments, which can lead to inconsistencies and delayed detection. This study proposes a systematic and reproducible machine learning framework for the classification of MDD using resting-state functional magnetic resonance imaging (rs-fMRI) data. Neuroimaging data are preprocessed using the DPABI toolbox, incorporating motion correction, spatial normalization, smoothing, nuisance regression, and band-pass filtering. Brain regions are defined using the Craddock 200 functional atlas, and regional time series are extracted to compute two forms of connectivity features: Static Functional Connectivity (SFC) and Dynamic Functional Connectivity (DFC). SFC captures time-averaged inter-regional correlations, while DFC models temporal variations using a sliding-window approach. High-dimensional features are reduced using Singular Value Decomposition (SVD), and classification is performed using a Support Vector Machine (SVM) with a radial basis function (RBF) kernel. Experimental results show that SFC achieves an accuracy of 0.690 and an AUC of 0.742, outperforming DFC, which achieves an accuracy of 0.655 and an AUC of 0.655. The findings indicate that static connectivity provides more stable and discriminative features for MDD classification in the given dataset. This work presents a transparent and reproducible pipeline that supports the development of objective neuroimaging-based diagnostic tools.

Keywords: Resting-state fMRI, Static Functional Connectivity, Dynamic Functional Connectivity, SVM

INTRODUCTION

Major Depressive Disorder (MDD) is one of the most prevalent and impactful psychiatric conditions, affecting emotional regulation, cognitive functioning, and overall well-being. It extends beyond temporary emotional distress and involves persistent disruptions in mood, executive processes, and physiological balance. Global health estimates indicate that approximately 300 million individuals are affected by depression, making it a leading contributor to disability worldwide.

A major challenge in diagnosing MDD lies in the reliance on subjective clinical assessments. Standard diagnostic frameworks and rating scales depend on clinician interpretation and patient self-reporting, which can introduce variability and reduce diagnostic consistency. This limitation highlights the need for objective, biologically grounded diagnostic approaches.

Resting-state functional magnetic resonance imaging (rs-fMRI) has emerged as a promising tool for identifying neural biomarkers of depression. It enables the measurement of spontaneous brain activity by capturing temporal correlations in Blood Oxygen Level-Dependent (BOLD) signals across different brain regions. These correlations reflect the brain's intrinsic functional organization and provide insights into large-scale neural networks associated with cognitive and emotional processes.

Previous studies have identified altered connectivity patterns in key brain networks in individuals with MDD, including the Default Mode Network, frontoparietal network, and limbic system. These alterations are associated with symptoms such as rumination, impaired cognitive control, and emotional dysregulation. Functional connectivity can be analyzed using two complementary approaches: Static Functional Connectivity (SFC), which captures time-averaged relationships between regions, and Dynamic Functional Connectivity (DFC), which reflects temporal variations in connectivity patterns.

Despite significant progress, several challenges remain, including limited sample sizes, variability in preprocessing methods, and potential confounding factors such as motion artifacts and demographic differences. This study addresses these limitations by proposing a standardized and reproducible machine learning pipeline for MDD classification using rs-fMRI data. The approach integrates consistent preprocessing, atlas-based feature extraction, and classification using

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Support Vector Machines (SVMs) to enable reliable and interpretable results.

MATERIALS AND METHODS

This study proposes a structured machine learning pipeline for the classification of Major Depressive Disorder (MDD) using resting-state fMRI data. The framework consists of preprocessing, feature extraction, dimensionality reduction, and classification.

All neuroimaging data are preprocessed using the DPABI toolbox to ensure consistency and reproducibility. The preprocessing steps include the removal of initial volumes to achieve signal stabilization, slice timing correction, motion correction using rigid-body transformation, spatial normalization to the Montreal Neurological Institute (MNI) template, spatial smoothing using a Gaussian kernel, nuisance signal regression, and band-pass filtering within the 0.01–0.08 Hz frequency range to retain meaningful neural signals.

Following preprocessing, brain regions are defined using the Craddock 200 functional atlas. For each subject, voxel-level BOLD signals within each region are averaged to obtain representative regional time series.

Two types of functional connectivity features are extracted. Static Functional Connectivity (SFC) is computed using Pearson correlation across the entire time series, resulting in a symmetric correlation matrix representing inter-regional relationships. Dynamic Functional Connectivity (DFC) is computed using a sliding-window approach, in which correlations are calculated over short temporal segments to capture time-varying connectivity patterns. Statistical measures such as the mean and variance across windows are used to summarize the dynamic features.

Due to the high dimensionality of the extracted features, Singular Value Decomposition (SVD) is applied for dimensionality reduction. The top components are retained to preserve the most informative variance while reducing the risk of overfitting. The features are standardized prior to classification.

Classification is performed using a Support Vector Machine (SVM) with a radial basis function (RBF) kernel. Model performance is evaluated using stratified *k*-fold cross-validation to ensure balanced representation of classes. Standard evaluation metrics, including accuracy and the area under the receiver operating characteristic curve (ROC-AUC), are used to assess classification performance.

RESULTS

The proposed framework was evaluated using both Static Functional Connectivity (SFC) and Dynamic Functional Connectivity (DFC) features for the classification of Major Depressive Disorder.

The SFC-based model achieved an overall accuracy of 0.690 and a Receiver Operating Characteristic Area Under the Curve (ROC-AUC) of 0.742. At the class level, healthy controls were identified with a precision of 0.71, a recall of 0.82, and an F1-score of 0.76. In contrast, MDD patients showed lower performance, with a precision of 0.65, a recall of 0.51, and an F1-score of 0.57.

The DFC-based model demonstrated comparatively lower performance, with an accuracy of 0.655 and a ROC-AUC of 0.655. Similar class-wise trends were observed, with stronger identification of healthy controls compared to MDD patients.

A comparative analysis indicates that SFC features provide more stable and discriminative representations than DFC features in the current dataset. The higher performance of SFC suggests that time-averaged connectivity captures more consistent patterns associated with MDD, whereas DFC introduces greater variability due to temporal fluctuations.

Overall, both approaches perform above chance level, confirming that functional connectivity features derived from rs-fMRI data contain meaningful information for MDD classification.

DISCUSSION

The results demonstrate that both static and dynamic functional connectivity features contain meaningful information for the classification of Major Depressive Disorder. However, static connectivity consistently outperforms dynamic connectivity in terms of both accuracy and ROC-AUC, indicating that time-averaged inter-regional relationships provide more stable and reliable discriminative features in this dataset.

The superior performance of Static Functional Connectivity can be attributed to its lower sensitivity to noise and reduced feature complexity. By aggregating connectivity patterns over the entire time series, SFC captures stable, trait-level alterations in brain networks, particularly within regions associated with the Default Mode Network and executive control systems. These findings are consistent with the existing literature, which reports persistent disruptions in these networks in individuals with depression.

In contrast, Dynamic Functional Connectivity captures temporal variations in brain activity, offering a more detailed representation of neural dynamics. However, this increased complexity results in higher feature dimensionality and greater variability across subjects, which can negatively impact model generalization, especially in datasets of limited size. As a result, the DFC-based model shows reduced performance compared to the SFC-based model.

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A notable observation is the disparity in classification performance between healthy controls and MDD patients. The model demonstrates higher recall for healthy controls, while performance for MDD patients is comparatively lower. This can be attributed to the clinical heterogeneity of depression, where diverse symptom profiles correspond to varied neural connectivity patterns, making consistent classification more challenging.

The study also emphasizes the importance of a standardized and reproducible pipeline. Consistent preprocessing, controlled feature extraction, and proper validation strategies contribute to reliable performance evaluation and reduce the risk of overfitting.

Overall, the findings highlight that, while both connectivity approaches are valuable, static connectivity provides a more robust foundation for classification in the current setting, whereas dynamic connectivity may require larger datasets or advanced modeling techniques to fully realize its potential.

CONCLUSION

This study presents a standardized and reproducible machine learning pipeline for the classification of Major Depressive Disorder using resting-state fMRI data. The proposed framework integrates preprocessing, atlas-based feature extraction, connectivity analysis, dimensionality reduction, and classification to enable objective evaluation of neural patterns associated with depression.

The results show that Static Functional Connectivity outperforms Dynamic Functional Connectivity, achieving higher accuracy and ROC-AUC. This indicates that time-averaged connectivity patterns provide more stable and reliable features for classification in the given dataset. In contrast, dynamic connectivity, while informative, introduces greater variability and requires more data or advanced modeling approaches to achieve comparable performance.

The observed difference in classification performance between healthy controls and MDD patients highlights the inherent heterogeneity of depressive disorders, which remains a challenge for consistent prediction.

Overall, this work demonstrates the potential of functional connectivity-based approaches for supporting objective, neuroimaging-driven diagnosis of MDD. The proposed pipeline provides a transparent and consistent foundation that can be extended in future research to improve classification performance and enhance clinical applicability.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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