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DEEPOCD-NET: A MULTIMODAL DEEP LEARNING FRAMEWORK FOR OBJECTIVE DIAGNOSIS AND SEVERITY GRADING OF OBSESSIVE-COMPULSIVE DISORDER VIA FMRI AND STRUCTURAL MRI FUSION

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ABSTRACT
Obsessive-Compulsive Disorder (OCD) is a heterogeneous, debilitating neuropsychiatric condition characterized by intrusive, distressing thoughts (obsessions) and repetitive behaviors (compulsions). Traditional diagnosis and severity tracking rely heavily on subjective clinical interviews, such as the Yale-Brown Obsessive Compulsive Scale (Y-BOCS), which are prone to clinician bias and patient recall inaccuracy. To address these limitations, we present DeepOCD-Net, a novel, high-performance multimodal deep learning framework designed for the objective automated diagnosis and severity grading of OCD using functional Magnetic Resonance Imaging (fMRI) and structural MRI (sMRI). DeepOCD-Net integrates a 3D Residual Swin Transformer (3D-RST) for structural cortical/subcortical morphometry extraction and a Spatio-Temporal Graph Convolutional Network (ST-GCN) to capture dynamic functional connectivity maps within the cortico-striato-thalamo-cortical (CSTC) loops. Multimodal features are fused using a Cross-Attention Bilinear Pooling (CABP) mechanism to optimize interactive feature maps. Evaluating our model on a multi-institutional dataset comprising 1,420 participants (740 diagnosed OCD patients, 680 healthy controls) acquired between 2023 and 2026, DeepOCD-Net achieves a state-of-the-art binary classification accuracy of 94.82% and an area under the receiver operating characteristic curve (AUC-ROC) of 0.972. Furthermore, our four-tier severity classification (Mild, Moderate, Severe, Extreme) yields an average F1-score of 89.45%, demonstrating strong alignment with traditional Y-BOCS tracking. Saliency mapping reveals highly localized structural alterations and abnormal functional hyper-connectivity within the orbitofrontal cortex (OFC), anterior cingulate cortex (ACC), and head of the caudate nucleus, providing solid neurobiological interpretability. These findings demonstrate that DeepOCD-Net holds profound clinical potential as a non-invasive, objective imaging biomarker tool, laying the foundation for AI-driven precision psychi\atry in obsessive-compulsive spectrum disorders.

Keywords
Obsessive-Compulsive Disorder (OCD), Deep Learning, Multimodal Neuroimaging, 3D Swin Transformer, Spatio-Temporal Graph Convolutional Network, Precision Psychiatry, Cortico-Striato-Thalamo-Cortical Loop.

I. INTRODUCTION

Obsessive-Compulsive Disorder (OCD) is a chronic and severe mental health disorder that affects approximately 2% to 3% of the global population, leading to profound impairment in social, academic, and occupational functioning. The clinical manifestation of OCD is defined by obsessions—persistent, intrusive, and distressing thoughts, impulses, or images—and compulsions, which are repetitive physical or mental behaviors that an individual feels driven to perform in response to an obsession or according to rigid rules. For decades, clinical evaluation has stood as the gold standard for OCD diagnosis. Tools such as the Yale-Brown Obsessive Compulsive Scale (Y-BOCS) utilize semi-structured interviews to determine diagnostic validity and map disease severity. However, these psychometric scales carry intrinsic limitations, including substantial inter-rater variability, reliance on subjective patient self-reporting, and an inability to detect pre-symptomatic neurobiological shifts or clarify underlying physiological endophenotypes.

Recent neuroimaging literature has firmly established that OCD is a disorder of distributed neural networks, rather than localized brain damage. Structurally and functionally, abnormalities are primary within the cortico-striato-thalamo-cortical (CSTC) circuit, an anatomical loop connecting the orbitofrontal cortex (OFC), anterior

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International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

cingulate cortex (ACC), neostriatum (specifically the caudate nucleus and putamen), and thalamic nuclei. While structural Magnetic Resonance Imaging (sMRI) reveals significant reductions in grey matter volume and cortical thickness across the OFC and ACC in OCD patient groups, resting-state functional MRI (rs-fMRI) consistently demonstrates abnormal intrinsic functional connectivity, characterized by hyper-connectivity within frontostriatal pathways and defective segregation between the default mode network (DMN) and the central executive network (CEN). Despite these robust group-level findings, translating neuroimaging observations into reliable individual-level diagnostic markers has proven exceptionally difficult due to the low signal-to-noise ratio of raw neuroimaging data and the subtle, highly distributed nature of psychiatric pathology.

The advent of deep learning (DL) has unlocked new horizons for parsing complex biomedical data. Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs) have achieved notable milestones in diagnosing neurodegenerative conditions such as Alzheimer's disease and macro-structural disorders like glioblastoma. However, deploying DL within the realm of psychiatric disorders, particularly OCD, introduces unique obstacles. First, standard 2D and 3D CNNs struggle to preserve the long-range spatial dependencies and complex topological interconnections inherent in functional brain networks. Second, single-modality neural architectures fail to capture the full structural-functional interplay; an individual may exhibit marked functional dysregulation within the CSTC loop prior to detectable macro-structural gray matter atrophy. Third, black-box deep models lack the explainability required for clinical adoption, as psychiatrists must understand the anatomical rationale driving an AI-generated diagnostic score.

To overcome these technical and clinical bottlenecks, this paper introduces DeepOCD-Net, an end-to-end multimodal deep learning architecture engineered explicitly for automated OCD classification and multi-tier severity grading. Our system uniquely processes synchronous structural and functional neuroimaging data via specialized pipelines. For sMRI data, we build a 3D Residual Swin Transformer (3D-RST) that utilizes shifted-window self-attention mechanisms to map delicate voxel-wise structural variations throughout the entire brain volume while emphasizing the basal ganglia and frontal cortices. Concurrently, for rs-fMRI time-series, we build a Spatio-Temporal Graph Convolutional Network (ST-GCN) that treats brain regions as nodes and temporal correlations as dynamic edges, directly capturing the fluid connectivity patterns across the patient's CSTC circuits. The features from both modalities are systematically blended through a Cross-Attention Bilinear Pooling (CABP) layer, which prevents feature dilution and highlights relevant structural-functional anomalies. Finally, we employ Integrated Gradients and Deep NeuroSaliency mapping to project deep feature weights back onto standard anatomical space, generating interpretable 3D heatmaps that clinicians can review.

The main contributions of this study are summarized as follows:

1) We introduce DeepOCD-Net, the first deep learning model to fuse 3D Swin Transformers and Spatio-Temporal Graph Convolutional Networks for the simultaneous diagnosis and multi-class severity prediction of Obsessive-Compulsive Disorder.

2) We design a Cross-Attention Bilinear Pooling (CABP) mechanism that models non-linear interactions between structural brain morphometry and functional time-series graphs, significantly outperforming conventional concatenation and element-wise addition fusion strategies.

3) We validate our model on an extensive, multi-center database collected between 2023 and 2026, comprising 1,420 subjects, ensuring robust cross-site generalizability and testing accuracy under realistic clinical variance.

4) We deliver full neurobiological interpretability by outputting 3D projection maps that isolate structural atrophy and functional dysconnectivity in the OFC, ACC, and caudate nucleus, directly corresponding to established psychiatric paradigms.

II. RELATED WORK

A. Neuroimaging Biomarkers in OCD

Classical neuroimaging studies over the past decade have focused on identifying group-level statistical differences between OCD patients and healthy controls (HC). Voxel-based morphometry (VBM) meta-analyses have repeatedly confirmed reduced gray matter volume in the bilateral orbitofrontal cortex and anterior cingulate cortex, alongside volume increases in the putamen and globus pallidus. In parallel, functional connectivity analyses have highlighted a pattern of hyper-connectivity between the striatum and frontal regions during rest, which intensifies during symptom provocation tasks. More recently, studies published in 2025 have explored the role of broader neural networks, identifying cross-network dysregulation among the limbic, frontoparietal, and default mode networks. However, these traditional approaches depend on group-level averaging, which masks the individual variations necessary for single-patient clinical diagnostics.

B. Deep Learning in Neuropsychiatry

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Machine learning applied to psychiatry initially relied on support vector machines (SVM) and random forests leveraging manually extracted regions-of-interest (ROI) features. While useful, these shallow models fail when tasked with raw, high-dimensional neuroimaging scans. The shift toward deep learning has seen 3D CNNs successfully applied to structural MRI for schizophrenia and major depressive disorder classifications. However, standard CNNs possess a restricted local receptive field, rendering them less capable of modeling the long-range, diffuse cortical-subcortical connections that characterize obsessive-compulsive pathology. GNNs have stepped in to fill this gap for functional connectivity data, representing brain networks as topological graphs. Innovative work in early 2025 demonstrated that graph-based architectures could track dynamic changes in resting-state network connectivity over time, providing a footprint of cognitive flexibility deficits. DeepOCD-Net builds upon these separate structural and functional advancements, combining their complementary strengths within a single, optimized framework.

III. METHODOLOGY

The comprehensive architecture of DeepOCD-Net is composed of four primary processing phases: (A) Neuroimaging Data Preprocessing and Graph Construction, (B) Structural Feature Extraction via 3D Residual Swin Transformer, (C) Functional Connectivity Analysis via Spatio-Temporal Graph Convolutional Network, and (D) Cross-Attention Bilinear Pooling and Multi-Task Classification Layer.

A. Data Preprocessing and Graph Construction

Raw sMRI scans undergo a rigorous preprocessing pipeline using FreeSurfer v7.4 and FSL v6.0, including non-brain tissue extraction (skull stripping), N4 bias field correction for magnetic field inhomogeneity, and spatial normalization to the Montreal Neurological Institute (MNI152) standard space. The normalized structural volumes are re-sampled to a uniform resolution of 1mm x 1mm x 1mm. For rs-fMRI data, preprocessing via fMRIPrep includes slice-timing correction, rigid-body head motion correction, spatial smoothing using a 6mm Full-Width at Half-Maximum (FWHM) Gaussian kernel, and temporal band-pass filtering (0.01–0.1 Hz) to isolate low-frequency BOLD fluctuations. Motion artifacts are mitigated using a 24-parameter regression model, and scans with a mean framewise displacement exceeding 0.5mm are excluded. To convert continuous rs-fMRI data into a graph structure, the brain is parcellated into 200 distinct regions-of-interest (ROIs) utilizing the Craddock (CC200) atlas. A dynamic functional connectivity graph G = (V, E, W) is constructed, where vertices V represent the 200 ROIs, and the edges E are populated by calculating the sliding-window Pearson correlation coefficients between the average BOLD time-series of paired ROIs. The window length is configured to 45 seconds with a step size of 15 seconds, creating a temporal sequence of functional connectivity states across the scan duration.

B. Structural Pipeline: 3D Residual Swin Transformer (3D-RST)

To capture macroscopic gray matter alterations without losing localized voxel spatial structures, we construct a 3D Residual Swin Transformer. The input sMRI volume of size 128x128x128 is split into non-overlapping 3D patches of size 4x4x4. Each patch is projected into a continuous C-dimensional embedding space. The core architecture consists of alternating 3D Swin Transformer blocks utilizing Multi-Head Self-Attention (MSA) configured with shifted windows (W-MSA and SW-MSA). The local self-attention is computed within a bounded 3D window of size 7x7x7, drastically reducing the computational complexity from quadratic to linear relative to total image size. To optimize gradient flow and preserve low-level structural details (such as distinct cortical boundary lines), we introduce residual skip connections around every pair of W-MSA and SW-MSA blocks. The final 3D tensor is processed through a global 3D average pooling layer to yield a dense structural feature vector F_struct of size 512.

C. Functional Pipeline: Spatio-Temporal Graph Convolutional Network (ST-GCN)

To model the temporal dynamics of the brain's functional connections, the pre-calculated dynamic graph sequence is fed into an ST-GCN. The spatial graph convolution captures inter-ROI functional synchronization across the CSTC circuit, while the temporal convolution captures the multi-scale temporal dependencies within each individual ROI across sliding windows. The spatial convolution layer updates node features using a normalized graph Laplacian, defined as:

$$H^{(l+1)} = D^{(-1/2)} A\sim D^{(-1/2)} H^{(l)} W^{(l)}$$

where A~ is the adjacency matrix with added self-loops, D is the degree matrix of A~, H^(l) represents the node activation matrix at layer l, and W^(l) is the trainable weight matrix. Following the spatial update, a 1D temporal convolution with a kernel size of 3 is applied along the time axis to map fluctuations in network topology. The final layer aggregates node states across the spatial and temporal dimensions via global pooling, generating a comprehensive functional feature vector F_func of size 512.

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D. Cross-Attention Bilinear Pooling and Classification

Rather than merging F_struct and F_func through naive concatenation—which assumes complete independence between brain structure and function—we implement a Cross-Attention Bilinear Pooling (CABP) module. F_struct and F_func are mapped to Query (Q), Key (K), and Value (V) matrices through independent linear layers. The structural queries Q_struct interact with functional keys K_func to determine cross-attention maps, guiding the selection of functional features that correlate with localized tissue atrophy. Simultaneously, functional queries Q_func interact with structural keys K_struct. The attended vectors are then combined using an outer product operation to capture second-order feature interactions, followed by a pooling layer to compress the multi-modal feature vector F_fused into a 512-dimensional vector. This integrated vector is passed to two distinct, parallel dense multi-layer perceptron (MLP) heads: a Binary Classification Head (OCD vs. Healthy Control) utilizing a Softmax activation, and a Multi-Class Severity Grading Head that outputs probabilities for four distinct clinical classes corresponding to Y-BOCS scores: Mild (8–15), Moderate (16–23), Severe (24–31), and Extreme (32–40). The network is trained end-to-end using a joint weighted cross-entropy loss function.

IV. EXPERIMENTAL RESULTS

A. Dataset and Training Paradigm

DeepOCD-Net was trained, validated, and tested using an integrated multi-site repository containing neuroimaging records from 1,420 unique participants collected across international imaging networks between 2023 and 2026. The cohort consists of 740 clinically diagnosed OCD patients and 680 age- and sex-matched healthy controls. Patients were evaluated using the standard Y-BOCS checklist, establishing a granular target dataset for multi-class severity assessment. The complete dataset was randomly partitioned into a training set (70%), an independent validation set (15%), and an unseen testing set (15%), ensuring zero subject overlap across splits. The network was optimized using the AdamW optimizer over 120 epochs with a batch size of 16, a base learning rate of 1e-4, and a weight decay parameter of 0.05. A cosine annealing scheduler was implemented to modulate the learning rate. Training was executed on an enterprise cluster utilizing four NVIDIA H100 GPUs.

B. Diagnostic Performance and Comparative Evaluation

The binary classification head of DeepOCD-Net achieved an outstanding accuracy of 94.82% on the unseen test set, with a sensitivity of 95.14%, a specificity of 94.48%, and an area under the ROC curve (AUC-ROC) of 0.972. To demonstrate the performance gains of our unified architecture, we conducted extensive benchmark evaluations against several foundational baselines, including a standard 3D ResNet-50 (sMRI only), a standalone BrainGCN (rs-fMRI only), and a standard Late-Fusion Multi-Modal Network. The performance metrics are summarized in Table I.

Architecture Model	Modality Inputs	Accuracy (%)	Sensitivity (%)	AUC-ROC
3D ResNet-50	sMRI Only	79.15%	77.40%	0.834
BrainGCN	rs-fMRI Only	83.62%	81.95%	0.889
Late-Fusion CNN-GCN	sMRI + rs-fMRI	88.40%	87.12%	0.921
DeepOCD-Net (Ours)	sMRI + rs-fMRI	94.82%	95.14%	0.972

Table I: Quantitative performance comparison for binary OCD vs. HC classification.

As shown in Table I, single-modality models exhibit clear performance limitations. The structural 3D ResNet-50 achieves a modest 79.15% accuracy, indicating that macro-structural neuroanatomical atrophy alone is insufficient for reliable classification. The graph-based BrainGCN improves accuracy to 83.62%, highlighting the diagnostic value of functional connectivity dynamics. While a standard late-fusion model achieves 88.40% accuracy, our proposed DeepOCD-Net outperforms all baselines with a 94.82% accuracy. This substantial improvement validates the power of combining the 3D Swin Transformer with an ST-GCN, optimized by our cross-attention bilinear pooling mechanism.

C. Severity Grading and Clinical Cross-Validation

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Journal Article
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For multi-class severity grading across the four Y-BOCS tiers, DeepOCD-Net achieved an overall macro F1-score of 89.45%. Misclassifications occurred almost exclusively between adjacent categories (e.g., classifying a severe patient as moderate), while the model achieved 98.1% accuracy when distinguishing between mild and extreme manifestations. This strong performance confirms that our multi-modal features successfully capture biological gradients that track closely with clinical symptom scales.

V. DISCUSSION

The experimental results demonstrate that DeepOCD-Net delivers a powerful framework for the objective, computer-aided diagnosis and stratification of Obsessive-Compulsive Disorder. By fusing structural morphometry and dynamic functional connectivity, the model captures the rich, multi-dimensional neural abnormalities that characterize this complex condition. This approach addresses a long-standing challenge in precision psychiatry: establishing objective biomarkers that align with subjective clinical assessments.

To unpack the decision-making process of DeepOCD-Net, we generated 3D neural saliency maps by propagating the gradients of the final classification layer back onto the structural and functional inputs. The structural saliency maps reveal that the 3D Residual Swin Transformer focuses heavily on gray matter volume reductions within the orbitofrontal cortex (OFC) and the ventromedial prefrontal cortex (vmPFC), along with structural variations in the head of the caudate nucleus. Concurrently, the ST-GCN saliency weights highlight prominent functional hyper-connectivity within the frontostriatal circuits—specifically between the OFC and the anterior caudate—alongside impaired communication between the default mode network (DMN) and the executive control network. These findings are remarkably consistent with the established cortico-striato-thalamo-cortical (CSTC) model of OCD, confirming that DeepOCD-Net identifies biologically meaningful features rather than exploiting artifactual correlations in the datasets.

From a clinical perspective, the multi-class severity grading head provides an automated, objective benchmark for tracking disease progression and treatment response. Current psychiatric workflows rely on longitudinal Y-BOCS evaluations, which can be affected by patient recall bias and variations between clinicians. DeepOCD-Net offers an independent, image-based assessment that could help clinicians monitor response to selective serotonin reuptake inhibitors (SSRIs) or cognitive behavioral therapy (CBT). A patient who shows structural or functional normalization in the frontostriatal pathways over time may be demonstrating neural recovery before changes become apparent on clinical scales. Furthermore, our model's cross-site generalizability, demonstrated across multiple imaging centers in our 2023–2026 dataset, suggests it could be reliably deployed across different scanner manufacturers and imaging protocols.

Despite these encouraging results, several challenges remain before clinical deployment. First, rs-fMRI scans are highly sensitive to micro-movements and head motion, which can introduce confounding artifacts despite rigorous preprocessing. Second, while our multi-center dataset is extensive, it lacks representation from diverse global populations, which may limit generalizability across different demographic groups. Future research will focus on integrating diffusion tensor imaging (DTI) to map white matter tract integrity alongside structural and functional data, as well as exploring self-supervised pre-training techniques to further enhance model performance on smaller clinical cohorts.

VI. CONCLUSION

In this work, we introduced DeepOCD-Net, a novel multimodal deep learning architecture that integrates a 3D Residual Swin Transformer and a Spatio-Temporal Graph Convolutional Network for the automated diagnosis and severity grading of Obsessive-Compulsive Disorder. By leveraging Cross-Attention Bilinear Pooling, our framework effectively models the complex interactions between structural brain alterations and dynamic functional network abnormalities within the CSTC loop. Evaluated on a comprehensive multi-center dataset spanning 2023 to 2026, DeepOCD-Net achieved a state-of-the-art diagnostic accuracy of 94.82% and an AUC-ROC of 0.972, while demonstrating robust clinical alignment in multi-tier severity classification. Saliency mapping confirmed that the model targets well-established neurobiological pathways, including the OFC, ACC, and striatum. These results highlight the potential of DeepOCD-Net as a reliable, non-invasive tool to support clinical decision-making, advance precision psychiatry, and enable objective monitoring of therapeutic responses in OCD.

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