Depression ravage the brain structure.

Finding the black dog.

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INTRODUCTION

Depression affects 280 million individuals worldwide, presenting a significant public health challenge. Current diagnostic tools, such as the Beck Depression Inventory-II (BDI-II), primarily rely on subjective self-reports that can be influenced by stigma and inaccuracies.

To address this limitation, our study explores the use of a deep learning-based approach to predict BDI-II scores from brain MRI scans, providing a potential biomarker-based solution.

RESULTS

The model achieved high scores on selected metrics **(Table 2, Fig. 3)**, demonstrating the capacity to provide reliable, non-invasive estimates of depression severity. Attention maps highlight the regions with the greatest impact on the predictions **(Table 5, Fig. 4-7)**.

DISCUSSION

This CNN-based approach offers a scalable diagnostic tool for mental health assessment, with the potential to enhance personalized treatment strategies.

However, further work is needed to:

- Access larger and more diverse MRI datasets for training.
- Validate the model across various populations and MRI protocols.
- Address the computational demands for large-scale implementation.

CONCLUSION

The proposed solution shows promise as an objective aid in diagnosing depression severity, which could improve clinical assessments and help reduce stigma. Continued research and development could pave the way for broader applications in mental health care.

METHODS

1. DATASET

The initial dataset consisted of over 700 sMRI scans, which were downsampled to 440 to ensure a balanced representation concerning the subjects' sex, age, and categorized BDI-II scores **(Table 1)**. The remaining 440 scans were then divided into training and testing sets in a 90/10 ratio.

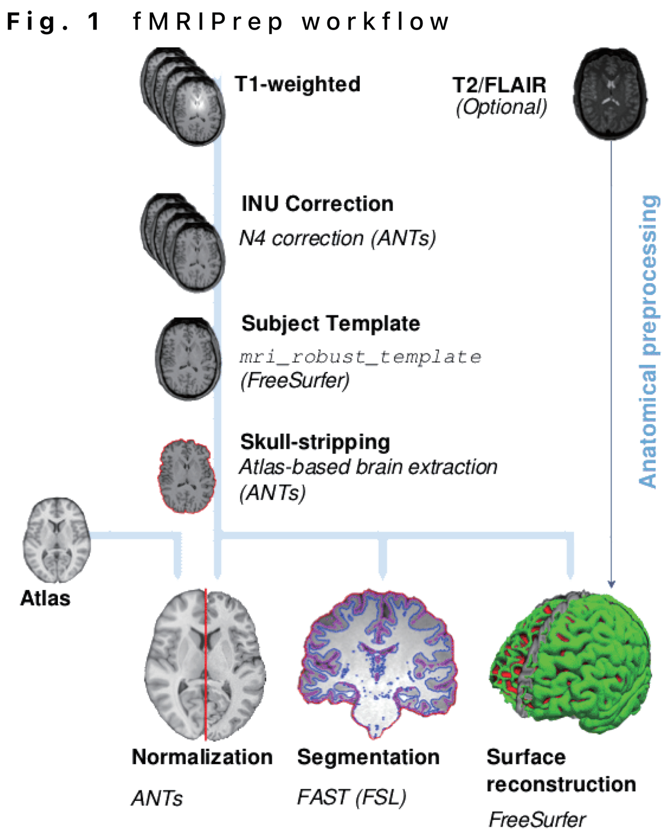
Table 1 Categorization of BDI-II scores

Label	Category	BDI-II
0	Minimal	0-13
1	Mild	14-19
2	Moderate	20-28
3	Severe	29-63

2. DATA PREPROCESSING

Raw structural MRI (sMRI) scans were preprocessed using the standardized fMRIPrep pipeline **(Fig. 1)**. Next, the scans were resampled to a 1 mm³ voxel size, intensity values were normalized, smoothed with a 3 mm filter, and any unnecessary empty space was cropped out.

Fig. 1 fMRIPrep workflow

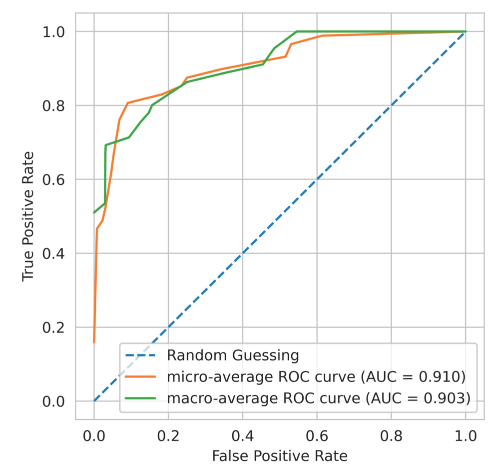


Source: fMRIPrep documentation

Table 2 Performance metrics

Metric	Averaging	Score
Accuracy	-	77.27%
Precision	Macro	84.93%
Recall	Macro	76.65%
F1-Score	Macro	77.99%
ROC-AUC	Macro	90.27%
	Micro	91.01%

Fig. 3 Multiclass ROC curve



3. MODEL ARCHITECTURE

A 10-layer convolutional neural network (CNN) based on the ResNet architecture was adapted for 3D input to analyze volumetric brain features **(Fig. 2, Tables 3-4)**. The model was trained using the Stochastic Gradient Descent algorithm with Cross-Entropy as the loss function.

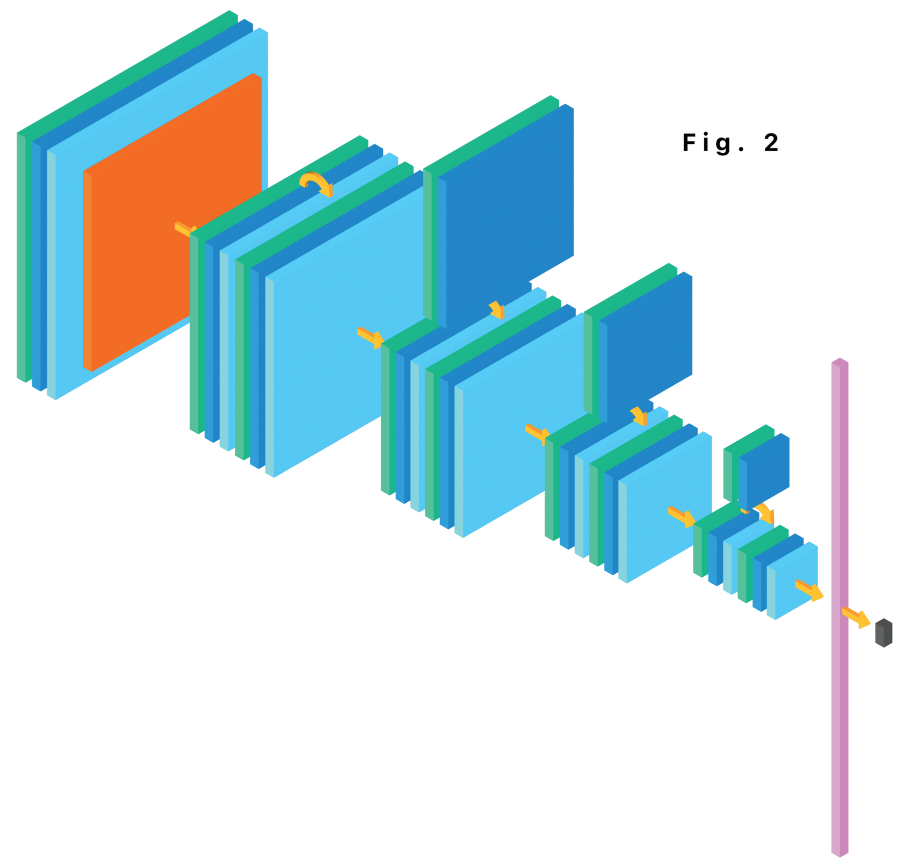


Fig. 2

Table 3 Model architecture

Stage
Convolution
ReLU
Max Pooling
ResNet Block 1
ResNet Block 2
ResNet Block 3
ResNet Block 4
Average Pooling
Fully Connected

Table 4 ResNet Block

Layer	Skip Connection
Convolution	
Batch Norm.	
ReLU	
Convolution	Convolution
Batch Norm.	Batch Norm.
ReLU	

Table 5 Brain regions with the greatest impact on the predictions

ROI (Region of interest)	Abbrv.	BA	AVG. ROI impact
Inferior Frontal Gyrus, pars triangularis	IFG-Tr	45	0.66
Inferior Frontal Gyrus, pars opercularis	IFG-Op	44	0.51
Middle Frontal Gyrus	MFG	46	0.38
Superior Temporat Gyrus, anterior divisio	STG-ant	22	0.34
Middle Temporal Gyrus, anterior division	MTG-ant	21	0.33

Fig. 4-5 Attention map and the most impactful brain regions

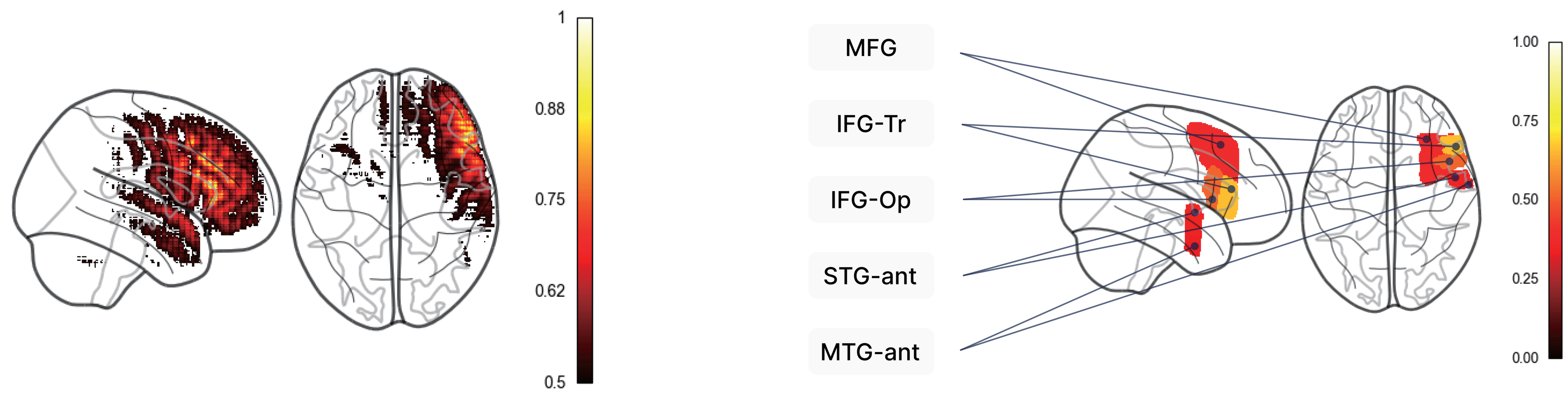


Fig. 6

Attention map on axial, sagittal and coronal planes

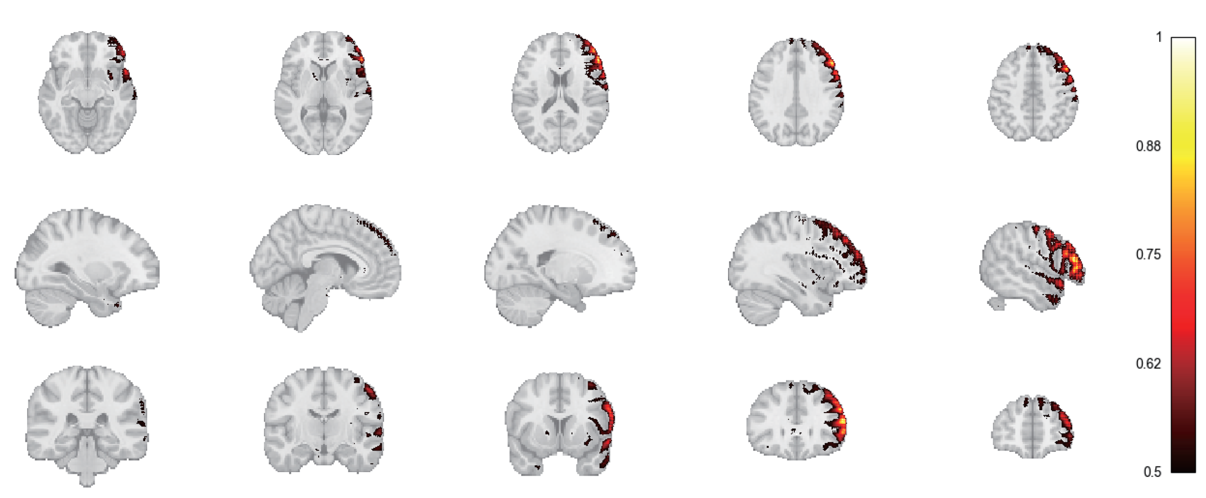


Fig. 7

Most impactful brain regions on axial, sagittal and coronal planes