

# A convolutional neural network-based autoencoder and machine learning model for identifying bipolar disorder patients using structural MRI features

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## Introduction

This study aims to predict disparities in brain images between individuals with bipolar disorder and those with normal brain function. Utilizing an unsupervised learning approach, we employ an autoencoder alongside diverse machine learning classification algorithms. Given the subjective nature of bipolar disorder diagnosis relying on clinical observation. Therefore, this project hopes to develop a programmed system that will assist in the early diagnosis of bipolar disorder and improve the accuracy and efficiency of the diagnosis.

## Materials and Methods

### Cases :

62 patients with Bipolar Disorder (23 Male, 39 Female, National Cheng Kung University Hospital), 62 normal people (26 Male, 36 Female, Community recruitment), totaling 124 patients.

### Machine Learning :

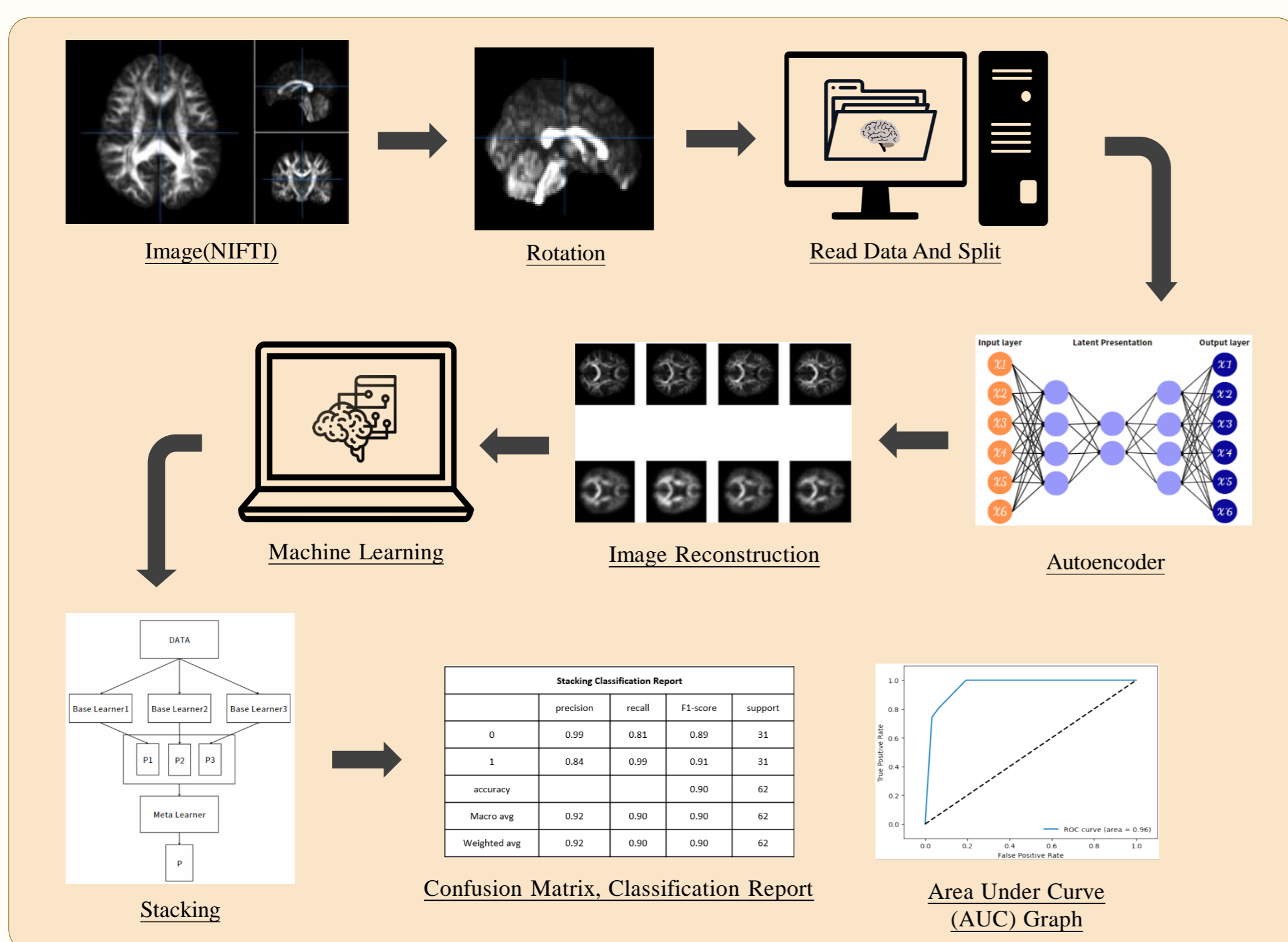
Random Forest (RF), ExtraTreesClassifier, GaussianProcessClassifier (GPC), logistic regression (LR), Extreme Gradient Boosting(XGB)

### Model Evaluation : Hold-Out method

### Image Parameters :

- (1) Magnetic field size: 3T
- (2) Repetition time (TR) / echo time (TE) = 8000/115 ms
- (3) Field of view (FOV) : 250 × 250 mm<sup>2</sup>
- (4) Matrix size = 128 × 128
- (5) Slices = 40, Slice thickness = 3 mm
- (6) In-plane resolution = 1.95 × 1.95 mm<sup>2</sup>
- (7) Signal average = 1
- (8) 96 noncollinear diffusion weighting gradient directions with b = 2500 s/mm<sup>2</sup>
- (9) 1 null image without diffusion weighting (b = 0 s/mm<sup>2</sup>)

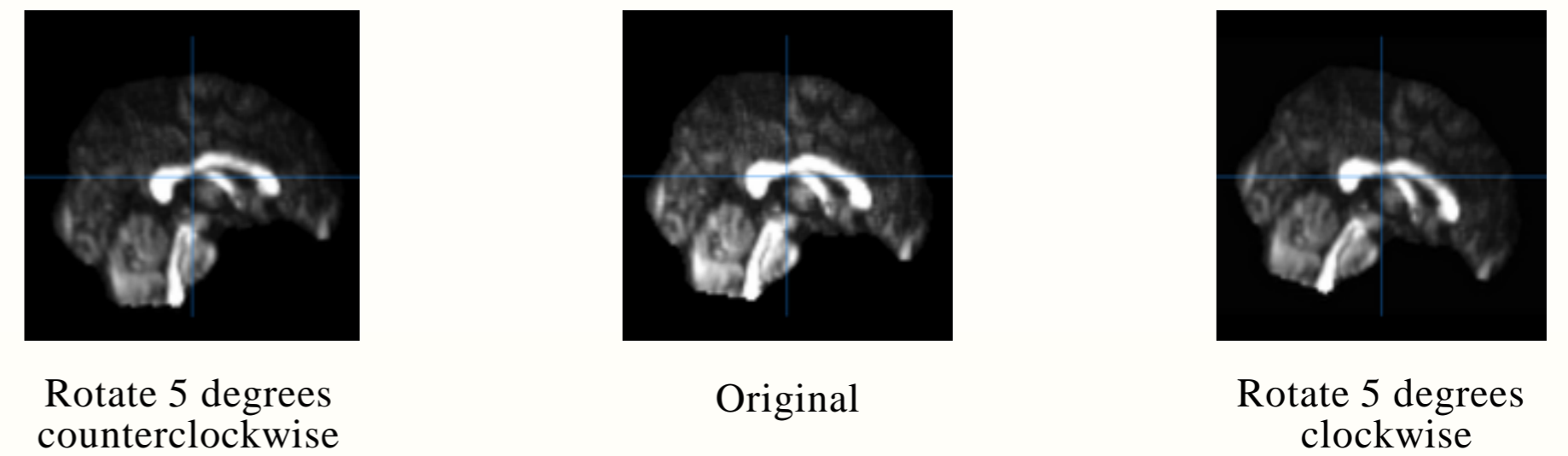
### System Flowchart :



In our study, we used magnetic resonance imaging (MRI) images of the brain combined with machine learning-based methods for analysis. First we performed Data Augmentation to expand our sample set. Using the Hold-out method to divide the data set into training set (80%), validation set (10%), and test set (10%) for training and evaluation of the model.

Next, we use an autoencoder encoder and decoder to capture subsequent image reconstruction functions. The model was trained by various machine learning methods and the parameters were tuned to achieve optimal performance. Evaluation involved stacking with logistic regression, and results are presented through confusion matrices, classification reports, and AUC graph.

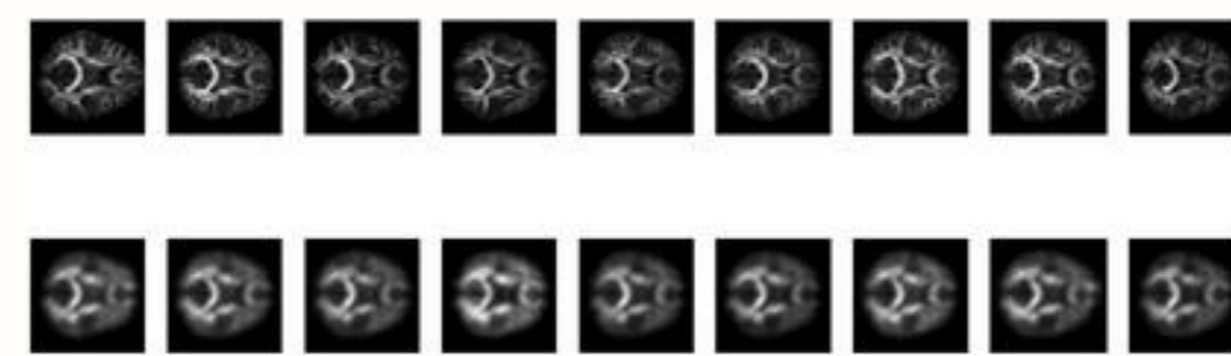
## Data Augmentation : Rotated (Example)



Rotate 1 degree clockwise & 2 degrees counterclockwise to add data.

- Bipolar Disorder patients 62 images -> 310 images
- Healthy control group 62 images -> 310 images

## Image Reconstruction

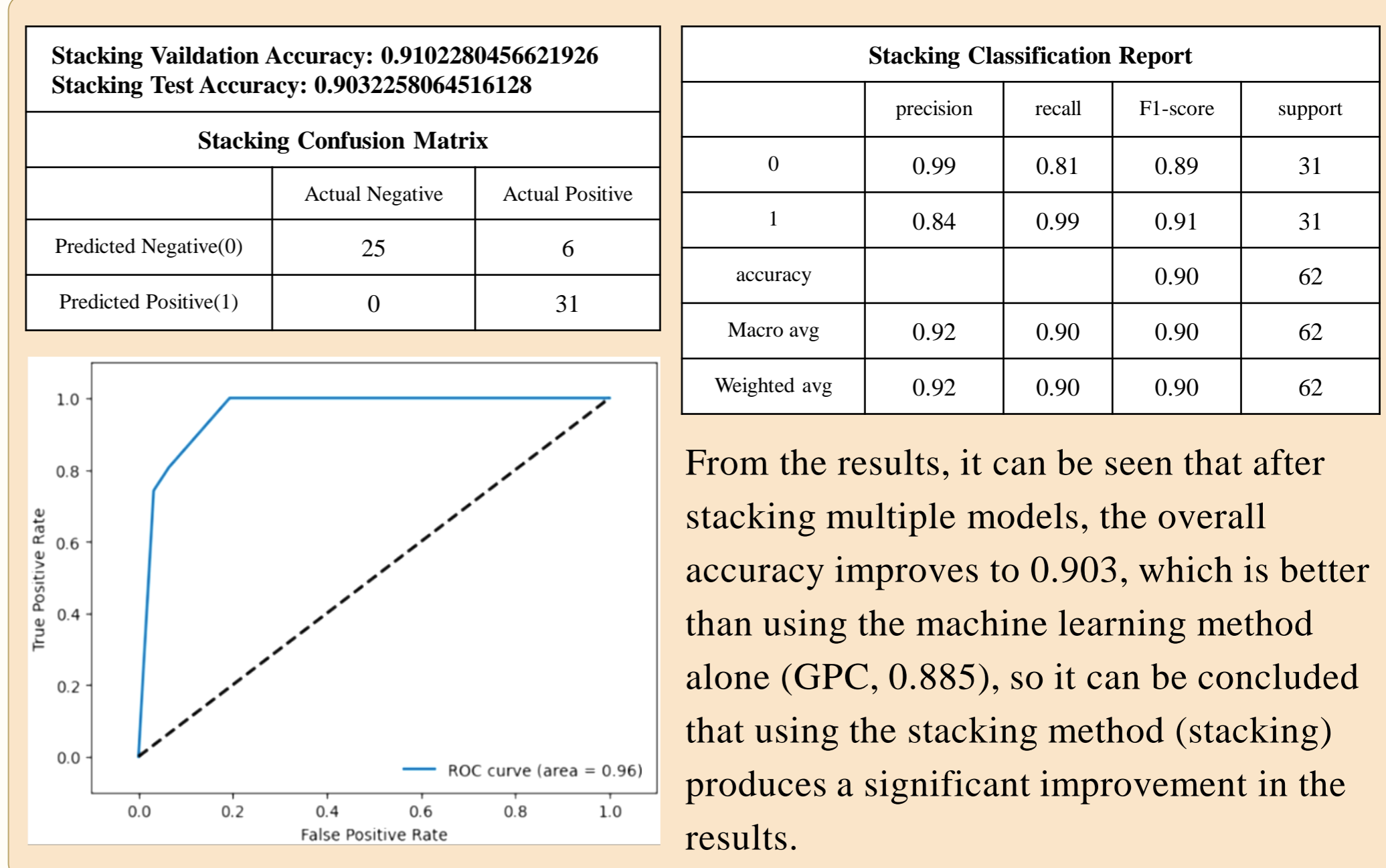


Using Autoencoder to get the data during decoding and start training the image, the reconstructed brain section will be displayed to confirm the completeness of the image.

## Result

	Validation_accuracy	Test_accuracy	ROC curve
RF	0.903	0.871	0.94
ExtraTreesClassifier	0.870	0.854	0.97
GPC	0.887	0.885	0.98
XGB	0.887	0.806	0.94

Different classifications achieved various performance metrics in the prediction. The final evaluation of the specified machine learning model is performed by stacking with logistic regression.



## Conclusion

Autoencoder and machine learning effectively predict brain images in bipolar disorder patients and normal individuals. Yet, further research is required for validation and optimization. Future studies should address sample size, classification parameters, and diverse ethnic characteristics to enhance the prediction model's accuracy and reliability, offering a more dependable tool for early bipolar disorder diagnosis.

## Reference

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