

Resting-State EEG Classification of Children and Adolescents Diagnosed With Major Depressive Disorder Using Convolutional Neural Networks

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Introduction

- Major Depressive Disorder (MDD) is a highly prevalent psychiatric disorder globally
- Timely identification and early detection of MDD plays a vital role in diagnostic and treatment
- Using EEG would potentially contribute to detect and correctly diagnose MDD
- Provide the correct treatment for patients, and help us better evaluate the different methods used for treating depression or help clinicians to further propose individualised treatment

Previous findings

- Studies reported significant differences in EEG pattern of adults diagnosed with MDD (e.g., changes in theta, alpha, beta...)
- No studies conducted with the aim to classify EEG activities in Children and Adolescents diagnosed with MDD compared to Healthy individuals

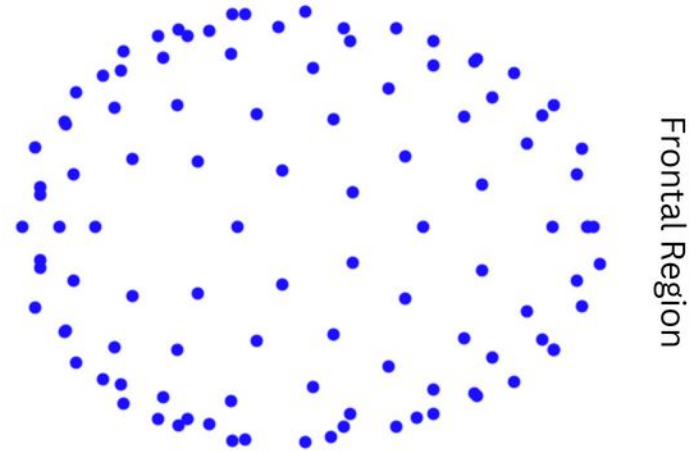


Research Question

Convolutional Neural Network (CNN) based on VGG16 model was used to identify biomarkers in Children and Adolescents with MDD from age-matched healthy young individuals

Methods & material: Dataset

- Provided by Healthy Brain Network (HBN) Institute
- Data is measured in the US on participant age 5-21
- Recording is done under resting-state, eyes closed condition
- 214 sample (MDD: 44, HBN: 170)
- 128 channels high density EEG (107 were retained for this study)



Methods & material: Pre-Processing

- Code available [here](#)
- Using PREP pipeline, bad channels are identified
- Resampling to 256 (500 originally)
- Band pass filter (1-70 Hz)
- Notch filter (60 Hz)
- Interpolation of bad channels
- Referencing based on average of channels
- Muscle movement, ECG and EOG artifacts were annotated
- ICA used to clean up bad artifacts and annotated bad artifacts

Methods & material: Pre-Processing

- Each EEG sample underwent filtering into distinct frequency bands (**Delta: 1-4 Hz, Theta: 4- 8 Hz, Alpha: 8-12, Beta: 12-30, and Gamma: 30-70 Hz**)
- Data is segmented into chunk, each is 4000 sample
- Each chunk is then resized into an image of size (107,350,3)

Methods & material: CNN-Architecture

- VGG16
- AdaBelief Optimizer and function loss Binary Cross Entropy
- Metrics: Accuracy, F1 score, Precision, Sensitivity, and Specificity

global_average_pooling2d (GlobalAveragePooling2D)	(None, 512)	0
flatten (Flatten)	(None, 512)	0
batch_normalization (BatchNormalization)	(None, 512)	2048
dense (Dense)	(None, 512)	262656
dense_1 (Dense)	(None, 512)	262656
dropout (Dropout)	(None, 512)	0
batch_normalization_1 (BatchNormalization)	(None, 512)	2048
dense_2 (Dense)	(None, 64)	32832
dense_3 (Dense)	(None, 1)	65

Total params: 15,276,993
Trainable params: 15,274,945
Non-trainable params: 2,048

Top layers of used architecture

Methods & material: Training

- Small dataset = 5840 samples with segmentation
- No improvement using SMOTE algorithm for the generation of additional data
- Overfitting: the model was trained using a subject-wise split + early stopping
- 5 K-fold cross-validation training
- Class weights were added to solve data imbalance

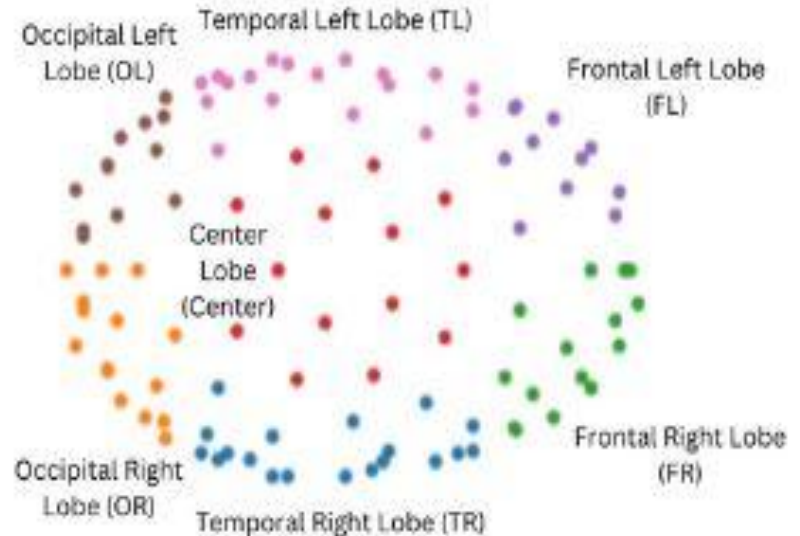
Region Of Interest (ROI)

Output:

- HBN bias (**high** specificity and **low** sensitivity)
- MDD bias (**low** specificity and **high** sensitivity)
- No Bias

Valid model:

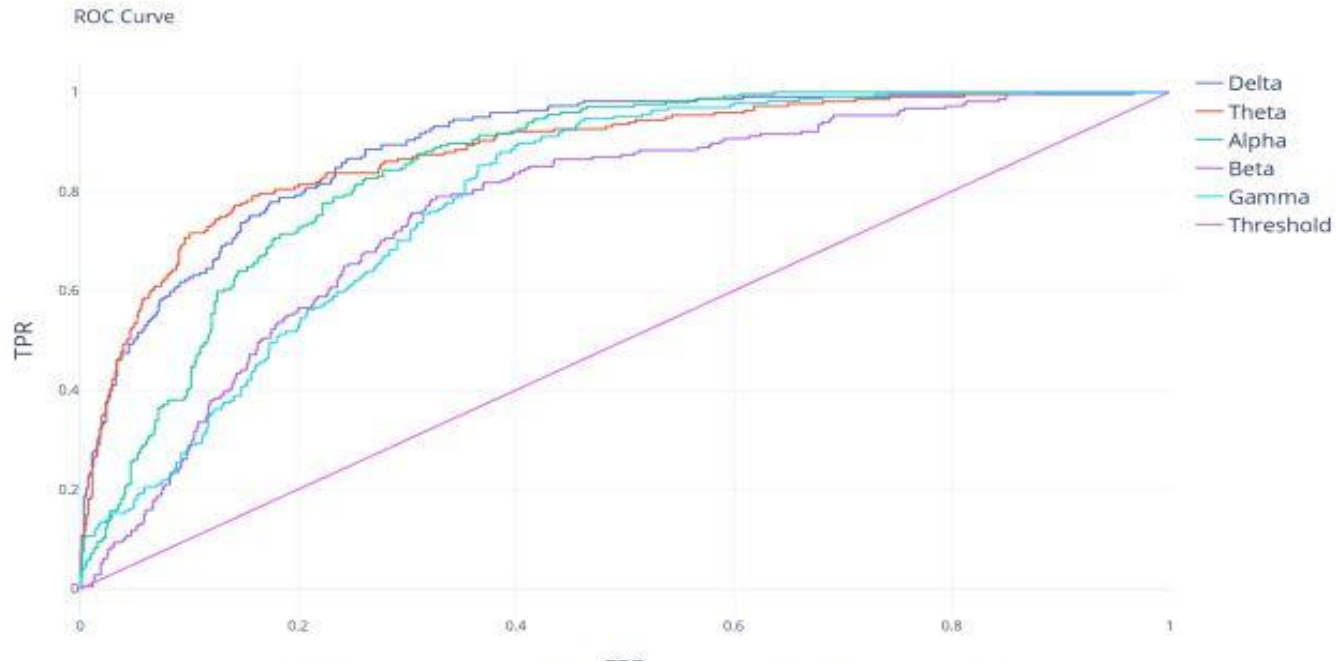
- Area Under Curve (AUC) score
- F1-Score



Results: Training Results

Frequency	accuracy	F1 Scores	Precision	Sensitivity	Specificity
All	0.875	0.638	0.643	0.693	0.923
Delta	0.856	0.539	0.686	0.467	0.955
Theta	0.895	0.717	0.659	0.826	0.907
Alpha	0.804	0.606	0.524	0.761	0.815
Beta	0.820	0.526	0.525	0.570	0.877
Gamma	0.744	0.399	0.350	0.501	0.800

Results: ROC and AUC scores

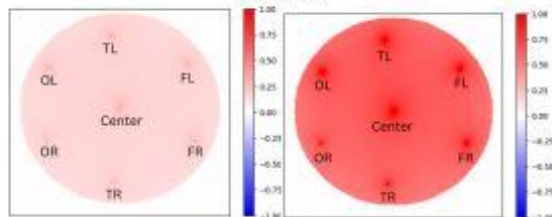


Frequency	Delta	Theta	Alpha	Beta	Gamma
AUC	0.890	0.881	0.848	0.763	0.788

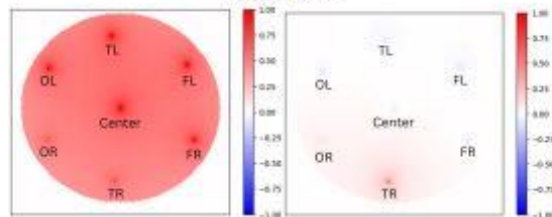
Cutoff for AUC is 0.80

Results: ROC

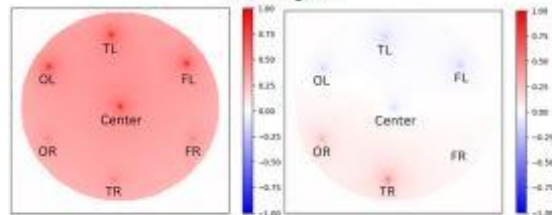
(a) Delta



(b) Theta



(c) Alpha



Freq	ROI	F1 Scores	Precision	Sensitivity	Specificity
Delta	TR	0.418	0.278	0.900	0.335
	OR	0.476	0.339	0.856	0.528
	FR	0.352	0.219	0.939	0.056
	Center	0.347	0.216	0.930	0.046
	FL	0.342	0.212	0.935	0.020
	OL	0.349	0.216	0.961	0.014
	TL	0.350	0.216	0.968	0.009
Theta	TR	0.405	0.265	0.974	0.369
	OR	0.421	0.380	0.517	0.817
	FR	0.045	0.145	0.028	0.999
	Center	0.001	0.001	0.001	1.000
	FL	0.001	0.001	0.001	1.000
	OL	0.001	0.001	0.001	0.997
	TL	0.001	0.001	0.001	0.999
Alpha	TR	0.387	0.248	0.944	0.256
	OR	0.403	0.284	0.768	0.490
	FR	0.411	0.397	0.480	0.793
	Center	0.065	0.194	0.040	0.981
	FL	0.001	0.001	0.001	1.000
	OL	0.001	0.001	0.001	1.000
	TL	0.001	0.001	0.001	1.000

Discussion

- Our results confirmed previous findings that delta, theta, and alpha are found to be associated with MDD symptoms.
- Theta waves are found to be associated with memory impairment and processes like working memory and episodic memory, as well as functions such as spatial navigation, attention and learning.
- Alpha activities are related to state of relaxation.

Discussion

- Delta activity and its role in MDD is related to patients with MDD having the habit of frequently introspecting and reflecting upon their self on a higher rate.
- Beta, unlike other studies, was found to be unrelated to MDD.

Conclusion

- MDD can be characterized by atypical delta, theta and alpha band activities
- The potential clinical applications of these differences in the delta band requires further research
- We encourage future studies to closely look at delta, theta and alpha activities
- Further investigation whether other frequency bands are involved in MDD before receiving any treatment (and co-existence of other disorders) amongst children and adolescents compared to healthy individuals.

