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Functional Connectivity Alterations in Major Depressive Disorder: Insights from EEG-Based Beta Band Connectivity Patterns

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***Abstract*—This paper compares the cerebral functional connectivity patterns of healthy and major depressive disorder patients by analyzing electroencephalogram recordings obtained during eyes-closed conditions in the beta-frequency band. Balanced and symmetrical connectivity was observed in healthy individuals' default mode network (DMN), indicating well-established brain function. Conversely, MDD patients showed increased connectivity in the frontal regions, whereas reduced connectivity was observed in the posterior brain regions. EEG-based functional connectivity analysis holds significant potential for a better understanding of the neurophysiological processes involved in this sector. Its application would also boost EEG integration with other technologies to continue searching for improved diagnostic accuracy.**

***Index Terms*—Functional Connectivity, EEG Analysis, Major Depressive Disorder (MDD), Default Mode Network (DMN), Functional Network (FN)**

I. INTRODUCTION

Major Depressive Disorder (MDD), commonly referred to as 'depression,' has been most prevalent among mood disorders. The name suggests that its attendants undergo constant sadness and loss of interest in most activities, accompanied by an alteration in cognitive functions [1]. According to the WHO, millions of people suffer from depression across the world. In their report from March 2023, the global prevalence of depression has increased to 5% of adults. Existing diagnostic tools like the beck depression inventory –II or BDI-2 depend on entirely subjective self-evaluation methods, which often lead to misdiagnosing patients [2][6]. They also fail to deliver any biological proof, relying entirely on a patient's self-reported feelings. On the other hand, EEG measurements offer significant potential for firsthand observation[8]. EEG identifies clear biological signs of MDD, such as unusual brain wave patterns and abnormal brain activity. This ensures earlier and more precise diagnosis and the tracking of the treatment effect through analyzing brain activity over time. Among EEG frequency bands, beta connectivity promises significant insights into MDD. Increased beta activity, particularly in parietal and temporal regions, has been repeatedly proven to be connected to heightened anxiety levels and depression[12][11].

II. MATERIALS AND METHODS

A. *Study Participants: MDD Patients and Healthy Controls*

The source of the datasets used for this research was obtained from a previous study [10], which included a group of thirty-three patients diagnosed with Major Depressive Disorder and a group of thirty healthy volunteers from Hospital Universiti Sains Malaysia (HUSM). MDD patients were assessed according to the diagnostic criteria for depression in the DSM-IV, while healthy participants were examined to exclude physical and psychiatric disorders.

III. DATA ACQUISITION: EEG RECORDING

The EEG data were recorded with a 19-channel EEG cap with a linked-ear (LE) reference. The 19 sensors are located at the following places: occipital (O1, O2) and frontal (Fp1, Fp2, F3, F4, F7, F8, Fpz), temporal (T3, T4, T5, T6), parietal (P3, P4, P7, P8), and central (C3, C4) [Figure-1].

A. *Data Preprocessing*

This study's raw EEG signals included noise from non-neuronal sources, such as eye movements and muscle activity.

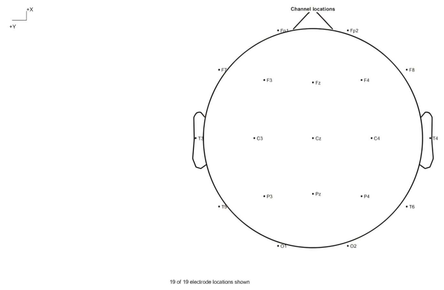

Fig. 1. 19 channel EEG cap locations

Such distortion can compromise the accuracy of the EEG data in representing the corresponding brain activity. Thus, Independent Component Analysis (ICA) was applied as a noise reduction method, allowing for the filtering of independent components. By examining the ICA maps, noisy components were identified and removed.

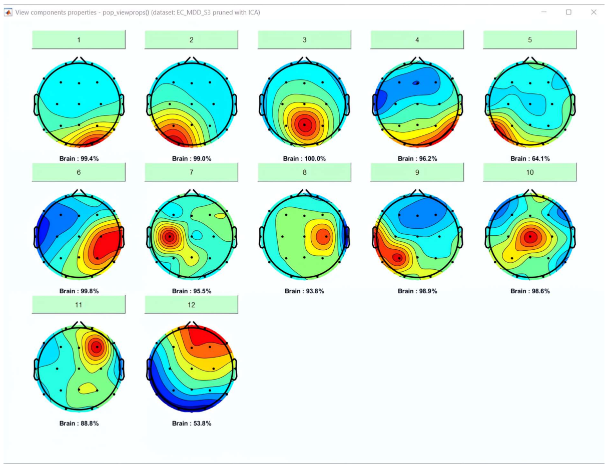

Fig. 2. Component properties after removing artifacts

B. *Functional connectivity*

For functional connectivity analysis, cleaned datasets of 7 healthy controls and 7 MDD patients in their eyes-closed(EC) state were run through simulation software to achieve their corresponding connectivity matrix [Figure-3] and connectivity band [Figure-4] within the beta frequency band. Therefore, the average beta power was calculated for every dataset.

CONNECTIVITY ANALYSIS FORMULA

Let M be the adjacency matrix where $M[i, j]$ is the strength of the connection between channels i and j. To determine the presence of a connection, we apply a threshold T:

$$C[i, j] = \begin{cases} 1 & \text{if } M[i, j] > T \\ 0 & \text{if } M[i, j] \leq T \end{cases}$$

C[i,j] is the binary connectivity matrix, with 1 indicating a connection and 0 indicating no connection.

Next, we construct a graph G where each EEG channel is represented as a node. An edge is created between channels i and j if $C[i, j] = 1$ and $i \neq j$:

$$G.add\_edge(\text{channel}_i, \text{channel}_j) \quad \text{if} \quad C[i, j] = 1 \text{ and } i \neq j$$

This results in a graph where the nodes represent EEG channels, and the edges represent significant connectivity based on the threshold T.

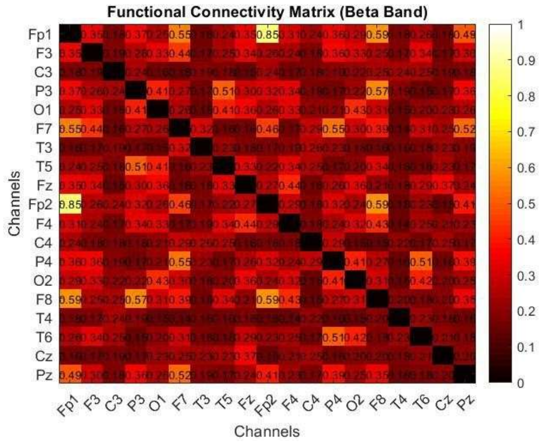

Fig. 3. Connectivity matrix

Figure 3: Description: The x- and y-axes represent EEG channels (Fp1, F3, C3, etc.) corresponding to electrode positions. Each pair of channels measures functional connectivity, with each cell indicating the connection strength between them

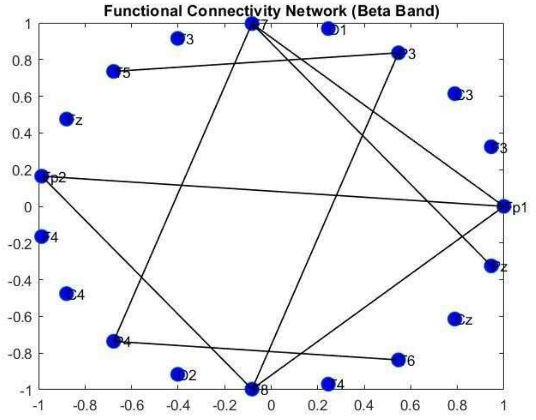

Fig. 4. Connectivity network

Figure 4: Description: The connectivity network shows functional connections between nodes (channels) based on Beta frequency brain activity.

IV. RESULT

A. *Functional Connectivity Patterns*

The connectivity between healthy individuals and patients suffering from MDD depicted some variations. Expressly, the connectivity deficits related to emotional regulation and memory processing among MDD patients were noted in the frontal and temporal areas[9][3]. On the other hand, there is beta connectivity increased in parietal-temporal areas that link with the elevated anxiety level commonly seen in MDD patients[5].

1) Functional Connectivity in Healthy Subjects (Eyes closed): For an individual healthy subject [e.g.(Figure-5)] under eyes-closed conditions, the connectivity graph shows robust and symmetric connections throughout frontal, temporal, and posterior areas. Particularly, nodes related to Default Mode Networks (DMN), such as Fp1, Fp,2, and Pz, exhibit high connectivity. It also refers to effective inter-network communication as it connects between temporal regions (T5, T6) and posterior areas (P3, O1)[4].

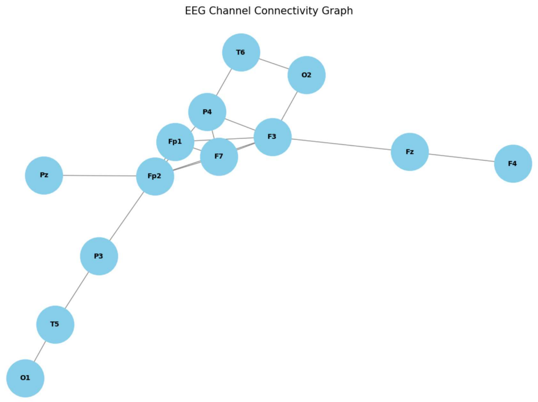

Fig. 5. Functional connectivity graph of an individual healthy control

2) Connectivity of healthy subjects in average: **Default Mode Network (DMN)**

The default mode network (DMN), represents a collection of distributed brain regions that oscillate coherently at low frequency during passive resting state when an individual is not focusing on external stimuli (Raichle et al., 2001).EEG connectivity graphs[e.g., (figure-5)] of healthy subjects display relatively strong and organized functional connectivity, especially in posterior (e.g., Pz, O1, O2) and frontal (e.g., F3, F4, Fp1) areas related to the DMN. They state what the brain does in its ordinary, deeply resting state. Thus, the connections appear balanced and symmetric.

Functional Network (FN)

Additional functional connections between temporal (T5, T6) and parietal (P3, P4) regions in Figure-6 highlight the involvement of other resting-state networks like the sensorimotor network (SMN) and visual network. The connectivity structure suggests a healthy balance between internal cognition and baseline external readiness.

3) Functional connectivity in MDD patients (eyes closed): In an individual MDD patient under eyes-closed conditions, the connectivity graph reveals prominent hyperconnectivity in frontal regions (e.g., Fp1, Fp2, Fz), reflecting heightened self-referential processing and rumination. Posterior connectivity, particularly involving Pz, O1, and O2, appears diminished, suggesting impaired introspective processing. Temporal-parietal connectivity, such as between T5 and P3, is notably weaker than healthy subjects, indicating reduced inter-network integration.

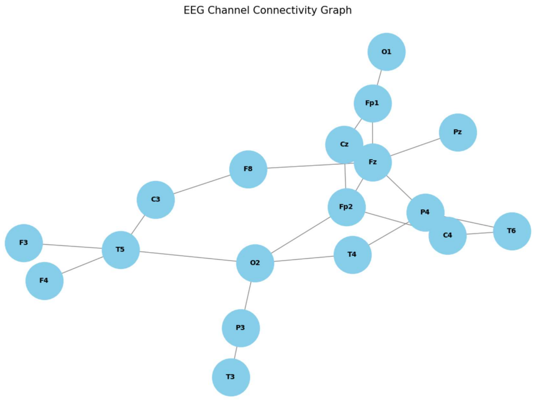

Fig. 6. Functional connectivity graph of average healthy control

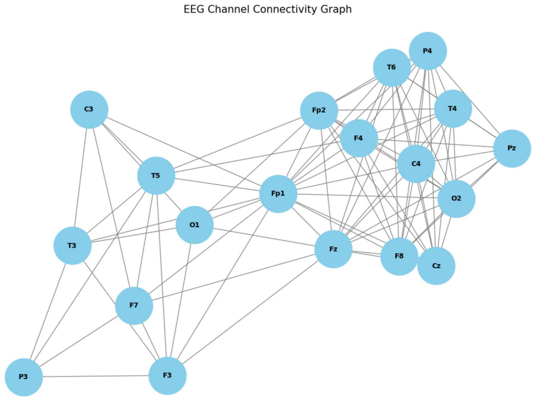

Fig. 7. Functional connectivity graph of an individual MDD patient

4) Connectivity of MDD patients in average: **Default Mode Network (DMN)**

The connectivity graph[Figure-8] for MDD patients under eyes-closed conditions indicates significant alterations in functional connectivity. Hyperconnectivity is observed in frontal regions, including Fp1, Fp2, and Fz, suggesting excessive self-referential processing and rumination, characteristic of depressive states. On the other hand, reduced connectivity in posterior regions, such as Pz, O1, and O2, indicates impaired introspective and reflective functions, commonly associated with MDD-related dysregulation in the DMN [7].

Functional Network (FN)

The graph further represents disturbed inter-network connections among the temporal (T5, T6) regions corresponding to the parietal (P3, P4) areas. This indicates a reduced capacity for functional integration, often associated with difficulties transitioning between internal (DMN) and external (FN) focus.

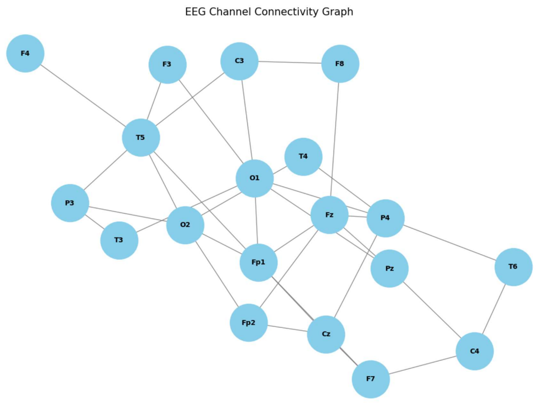

Fig. 8. Functional connectivity graph of average MDD patient

B. Comparison: Healthy vs. MDD (Eyes Closed)

Default Mode Network (DMN)

Healthy subjects contain robust and balanced DMN connectivity, indicating optimal communication within the network. In contrast, MDD patients show hyperconnectivity in frontal regions (Fp1, Fp2) and reduced connectivity in posterior regions (Pz, O1, O2). This imbalance shows that people with MDD tend to focus more on self-referential thoughts, which affects their ability to reflect inward effectively.

Functional Network (FN)

Healthy subjects also contain integrated functional connectivity between temporal (T5, T6) and parietal (P3, P4) regions, representing a balanced interaction between resting-state networks. In MDD patients, these connections are weaker, indicating reduced adaptability and impaired functional integration.

Overall Connectivity Pattern:

Healthy individuals show a symmetric and well-organized connectivity graph, supporting a dynamic balance between internal and external processing. In contrast, MDD patients display dysregulated connectivity, characterized by excessive internal focus and reduced functional flexibility.

V. DISCUSSION

Functional connectivity analysis reflected an ability to diagnose Major Depressive Disorder (MDD). Connectivity metrics across beta bands show alterations in their connectivity metrics that were associated in the past with recognized neurophysiological impairments in MDD. By expanding the sample size for future studies, the current research findings can be converted into something that would assess variation in connectivity analysis. Such data can be utilized to merge EEG further with other modalities, such as fMRI, to improve diagnostic accuracy and give insightful measures for MDD.

VI. CONCLUSION

Examining functional connectivity in EEG data provides a valuable, non-invasive method for diagnosing MDD. The distinct connectivity patterns observed between MDD cases and healthy individuals highlight the applicability of this method in clinical settings. Continuous research is essential to enhance these methods and ensure smooth incorporation into routine psychiatric practice.

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