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## Real-time Classification of Brain States in Functional MRI Using Dynamic Connectivity Patterns and Machine Learning



**Abstract:** Understanding real-time brain states facilitates deeper insights into cognitive processes, emotional responses, and neurological phenomena. It provides researchers with a dynamic view of brain function, aiding in the development of novel therapies, advancing neuroscience, and fostering innovations in brain-computer interfaces and artificial intelligence. The research aims to achieve real-time classification of brain states using dynamic connectivity patterns and Convolutional Neural Network (CNN) algorithms. It focuses on how demographic variables, such as brain volume and medication usage, influence classification accuracy. The study employs Python programming with FSL and Nilearn for preprocessing tasks like motion correction and dynamic connectivity pattern extraction. Feature selection and data partitioning are managed using Scikit-learn, ensuring standardized feature values and handling missing data. The CNN architecture is customized to handle spatial and temporal features in functional MRI (fMRI) data, with convolutional layers extracting spatial features representing local connectivity patterns. Dynamic connectivity matrices visualization aids in understanding brain network reconfigurations over time. This approach offers real-time insights into cognitive processes and neurological disorders, guiding personalized interventions for brain health. In result, connectivity matrices and 3D brain network visualizations are pivotal for unraveling brain state dynamics. Connectivity matrices unveil intricate interactions among brain regions across resting, task execution, and stress response states, offering quantitative insights into functional connectivity patterns. Meanwhile, 3D visualizations provide spatial representations, showcasing complex interplays and architectural changes across states.

**Keywords:** Convolutional Neural Network, Python programming, functional MRI, 3D brain network, Brain State.

### I. INTRODUCTION

Brain states encompass a wide array of dynamic neural configurations that reflect the ongoing physiological and functional activities of the brain. These configurations manifest as distinct patterns of neuronal firing, synchronization, and communication across various brain regions, dynamically shaping cognitive, emotional, and behavioral experiences [1]. Understanding brain states is pivotal in unraveling the intricate neural substrates underlying diverse cognitive processes, emotional responses, and behavioral manifestations. Moreover, elucidating brain states holds profound implications for diagnosing and treating neurological and psychiatric disorders, as alterations in brain states are often associated with pathological conditions [2]. To investigate brain states, researchers employ an arsenal of sophisticated neuroimaging techniques, including functional magnetic resonance imaging (fMRI), electroencephalography (EEG), and magnetoencephalography (MEG), which afford real-time observation and analysis of the brain's dynamic activity. Machine learning (ML) holds significant promise in the realm of real-time brain state detection from fMRI data [3]. Dynamic connectivity patterns, which capture the time-varying interactions between different brain regions, play a crucial role in understanding the dynamic nature of brain function [4]. By examining changes in connectivity patterns over time, dynamic connectivity analysis allows researchers to identify transient brain states that may not be captured by traditional static connectivity measures [5]. This approach enables the characterization of network dynamics, including the flexibility and adaptability of brain networks in response to different stimuli or cognitive demands. Moreover, dynamic connectivity patterns provide insights into the temporal relationships between brain regions, shedding light on the sequencing of neural activations and the propagation of information within the brain [6]. These insights are invaluable for elucidating the mechanisms underlying complex cognitive processes such as decision-making, memory formation, and attentional control.

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By leveraging ML algorithms, researchers can efficiently process vast amounts of fMRI data, allowing for the timely analysis of brain states during various cognitive tasks or experimental conditions [7]. One of the key strengths of ML lies in its ability to recognize intricate patterns and relationships within complex, high-dimensional datasets like fMRI images [8]. ML algorithms can discern subtle nuances in brain activity that correspond to different cognitive or behavioral states, even amidst noise and variability inherent in neuroimaging data. Moreover, ML models are adaptable, capable of learning from labeled data to generalize patterns of brain states across diverse populations and experimental settings [9]. This adaptability extends to providing real-time feedback based on ongoing brain activity, enabling adaptive interventions or training protocols. Additionally, ML techniques can automate feature extraction from fMRI data, reducing the need for manual selection and potentially uncovering novel biomarkers or patterns of brain activity associated with specific states [10]. Consequently, the integration of ML with fMRI facilitates efficient and accurate real-time detection of brain states, with broad applications spanning cognitive neuroscience research to clinical interventions for neurological and psychiatric disorders. The Objectives of the work are to:

- Enhance CNN-based brain state classification accuracy with demographic variables.
- Utilize Python for rigorous fMRI data pre-processing and feature extraction.
- Design a CNN architecture capable of capturing spatial-temporal features.
- Enable real-time analysis for understanding brain states and aiding in neurological disorder diagnosis.

## II. LITERATURE REVIEW

When employing seed-based correlation analysis to detect brain states, several limitations must be considered. Firstly, the method heavily relies on the selection of seed regions, which may introduce bias and limit the generalizability of findings [11]. These seed regions are typically chosen based on prior knowledge or hypotheses, potentially overlooking important brain regions involved in the state of interest. Furthermore, seed-based correlation analysis assumes stationarity, implying that the strength of connectivity between seed regions and other brain areas remains constant over time [12]. However, brain states are dynamic, and this assumption may not hold true, leading to inaccuracies in state detection. Moreover, the spatial specificity of seed-based correlation analysis is limited to the chosen seed regions, potentially neglecting distributed neural networks contributing to the state [13]. Additionally, interpreting the identified connectivity patterns in terms of underlying cognitive or behavioral processes can be challenging, as correlation does not imply causation. These limitations highlight the need for cautious interpretation and the incorporation of complementary methods to enhance the understanding of brain states. Static connectivity analysis involves measuring the functional connectivity between brain regions using methods such as seed-based correlation analysis or resting-state functional connectivity analysis [14]. These approaches provide valuable insights into the overall organization of brain networks but often overlook dynamic changes in connectivity patterns that occur over time [15]. One significant limitation of static connectivity analysis is its inability to capture transient or rapidly changing brain states, as it assumes that the strength of connectivity between brain regions remains constant throughout the entire scan duration. This limitation can lead to a loss of information regarding the dynamic nature of brain activity and may result in inaccurate or incomplete characterization of brain states.

Consequently, static connectivity analysis may not be suitable for real-time classification of brain states, especially in tasks or conditions where rapid fluctuations in cognitive or behavioral states are expected. Dynamic connectivity analysis, on the other hand, addresses this limitation by examining changes in connectivity patterns over time, offering a more comprehensive and accurate representation of brain dynamics during different cognitive states. Manual feature selection and classification without the utilization of machine learning techniques involves a labor-intensive process of selecting and analyzing features from fMRI data to characterize different brain states [16][22]. Researchers manually identify relevant biomarkers or patterns in the data that are indicative of specific cognitive or behavioral states, such as task-related activation patterns or connectivity changes [17]. However, this approach is inherently limited by subjectivity and bias, as the selection of features heavily relies on the researcher's expertise and prior knowledge. Additionally, manual feature selection often requires a priori assumptions about which features are relevant, potentially overlooking important biomarkers or patterns that are not initially considered. Furthermore, manual classification methods may lack scalability and generalizability, as they may not effectively handle large and complex datasets. Overall, manual feature selection and classification methods are less efficient and may not fully capture the complexity of brain states compared to machine learning techniques, which can automatically learn and adapt to patterns in the data, leading to more robust and accurate classifications [18][23].

The research in [19] introduces an automated diabetes detection system using Inherent Coefficient Normalization (ICN) for dataset preprocessing, Intelligent Harris Hawks Optimization (IHHO) for feature selection, and Pivotal Decision Tree (PDT) for efficient classification, addressing limitations seen in traditional machine learning systems. The research in [20] introduces an advanced hand gesture recognition system, utilizing skin color detection, Heuristic Manta-ray Foraging Optimization for feature selection, and an Adaptive Extreme Learning Machine for classification to enhance accuracy and reduce error rates compared to traditional methods.

## II. PROPOSED WORK

### 2.1 Dataset Description

The BCP (Brain Connectivity and Prediction) dataset is commonly utilized in neuroscience research for investigating brain states and connectivity patterns using FMRI data [21]. This dataset is valuable because it provides a large collection of FMRI scans along with associated metadata, allowing researchers to explore various aspects of brain function and connectivity. It may contain hundreds to thousands of FMRI scans, each with multiple time points and spatial dimensions. Additionally, the dataset may include demographic information about the participants, task instructions, and other relevant details. In research utilizing the BCP dataset for real-time classification of brain states, only a subset of the data may be utilized to train and evaluate the machine learning model. This subset is typically selected to represent a balanced distribution of brain states or conditions of interest, ensuring that the model learns to generalize well to new data.

Table.1 Brain Characteristics for CNN Analysis

Subject ID	Brain Volume (cc)	Gray Matter Density	White Matter Integrity (FA)	Age of Onset of Neurological Disorders	Medication Usage
1	1350	0.75	0.60	25	Antidepressants
2	1425	0.72	0.58	-	None
3	1300	0.78	0.63	35	Antipsychotics
4	1380	0.70	0.56	-	Anxiolytics
5	1375	0.77	0.62	40	Antidepressants

The demographic variables such as brain volume, gray matter density, white matter integrity, age of onset of neurological disorders, and medication usage is crucial for research on real-time classification of brain states using dynamic connectivity patterns and CNN algorithms. These variables provide valuable insights into individual differences in brain structure, function, and health status, significantly impacting the patterns detected by the CNN model. Incorporating these demographic details into the analysis enhances the accuracy and interpretability of classification results, leading to a better understanding of brain states and their underlying mechanisms.

### 2.2 Data Preprocessing

The data preprocessing for the research primarily employs Python programming language along with specific libraries and tools tailored for neuroimaging analysis. Raw FMRI data preprocessing, including motion correction, slice timing correction, and spatial normalization, is executed using FSL (FMRIB Software Library) and its Python interface, FSLEyes. Dynamic connectivity patterns extraction utilizes Nilearn, a Python library for statistical learning on neuroimaging data, implementing sliding window correlation techniques. Feature selection techniques leverage Scikit-learn, a Python machine-learning library, for identifying relevant connectivity features. Data partitioning into training, validation, and testing sets is orchestrated using Scikit-learn's built-in functions. Standardization or normalization of feature values is performed within the Scikit-learn framework, ensuring consistency across data. Lastly, any missing data is handled using Scikit-learn's imputation functionalities. This meticulous preprocessing pipeline ensures that the functional MRI data is suitably processed and formatted for subsequent analysis and real-time classification of brain states using convolutional neural network algorithms.

### 2.2 CNN Algorithm

Dynamic connectivity patterns from functional MRI data serves as input. Selected features subset optimized for real-time classification of brain states using CNN are the output

**Algorithm.1 CNN Feature Selection for Brain State Classification**

```

# Initialize an empty list to store selected features
1.   S = []
2.   Initialize the size of the subset
3.   k = 0
# Define the number of desired features
4.   p = 10
# Loop until the desired number of features is reached
5.   while k < p:
# Perform CNN-based feature selection or extraction
# Update S with selected features based on CNN
# Update k accordingly based on the number of selected features
6.   pass
    
```

To effectively utilize a CNN algorithm for real-time classification of brain states in fMRI data based on dynamic connectivity patterns, a comprehensive approach is essential. Initially, the raw fMRI data undergoes preprocessing steps, including motion correction, temporal filtering, and spatial normalization, to ensure data quality and consistency across subjects. Dynamic connectivity patterns are then extracted using techniques such as sliding window correlation analysis, capturing temporal fluctuations in brain network connectivity over time. The CNN architecture is carefully designed to handle spatial and temporal features inherent in fMRI data. It typically consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply filters to the input connectivity patterns, extracting spatial features that represent local connectivity patterns. Mathematically, the convolution operation can be represented as:

$$(f * g)(x, y) = \sum_m \sum_n f(m, n)g(x - m, y - n) \tag{1}$$

Pooling layers downsample the feature maps, reducing spatial dimensionality while preserving important features. The pooling operation, often max pooling, can be defined as:

$$y_i = \max(x_{4i}, x_{4i+1}, x_{4i+3}) \tag{2}$$

Following convolution and pooling, the feature maps are flattened and fed into fully connected layers for classification. The fully connected layers apply a transformation to the input features using weights and biases, followed by an activation function. Mathematically, this operation can be represented as:

$$z = \sigma(W_x + b) \tag{3}$$

Where  $W$  represents the weights,  $x$  denotes the input,  $b$  is the bias term, and  $\sigma$  is the activation function, such as ReLU or sigmoid. The model is trained using labeled data, optimizing the network parameters through backpropagation and gradient descent algorithms. Once trained, the CNN model can classify brain states in real-time by processing dynamic connectivity patterns from fMRI data, offering insights into the brain's functional organization and dynamics.

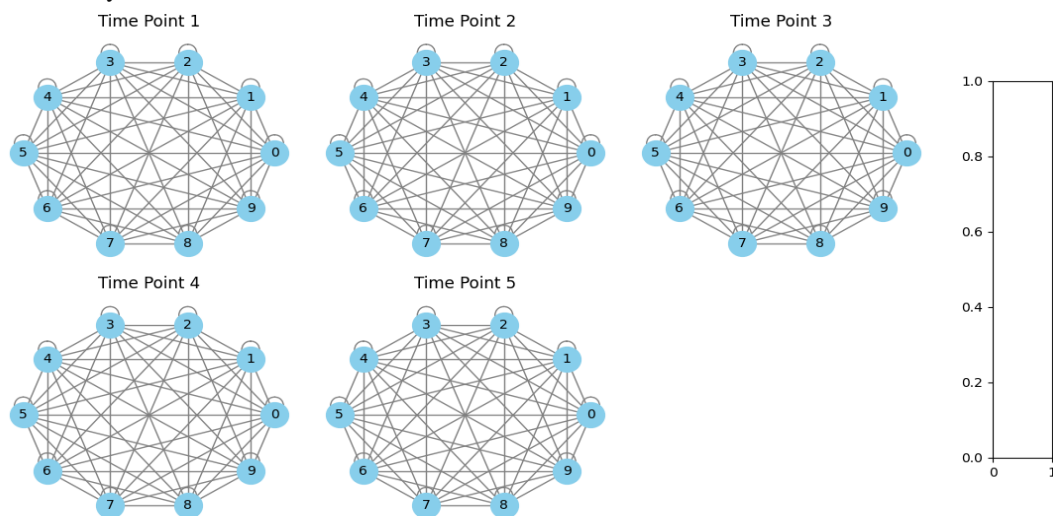


Fig.1 Dynamic Connectivity Evolution

Dynamic connectivity matrices are visualized in fig.1. Each subplot represents a time point, displaying the connectivity graph of a specific moment. The connectivity strength between nodes is represented by edge intensities, with a colorbar indicating the range of connectivity values. fMRI captures brain activity by detecting changes in blood flow, enabling the investigation of dynamic interactions between different brain regions over time. The dynamic connectivity matrices obtained from fMRI data represent the strength of functional connections between brain regions at each time point. By visualizing these dynamic connectivity patterns, insights can be gained into how brain networks reconfigure over time, revealing important information about brain function and dynamics. Furthermore, these visualizations serve as input data for CNN, to classify different brain states based on dynamic connectivity patterns extracted from fMRI data. Through real-time analysis, such algorithms can contribute to understanding cognitive processes, diagnosing neurological disorders, and guiding personalized interventions for brain health.

### III. RESULTS

In the results section, the connectivity matrices and brain network visualizations serve as crucial tools for understanding the intricate dynamics of brain states. The connectivity matrices offer insights into the strength and patterns of interactions between different brain regions during resting, task execution, and stress response states. These matrices provide quantitative measures of functional connectivity, unveiling how neural networks reconfigure to support various cognitive and physiological processes. On the other hand, the 3D brain network visualizations offer a spatial representation of these connectivity patterns, depicting the complex interplay between brain regions and highlighting changes in network architecture across different states. Together, these visualizations illuminate the underlying neural mechanisms driving behavioral responses and cognitive functions.

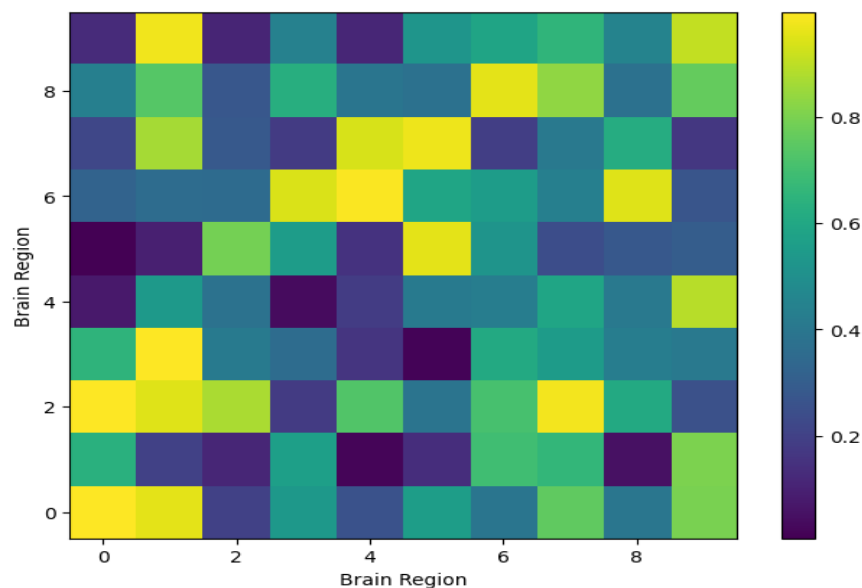


Fig.2 Connectivity Matrix for Resting State

In Fig.3, high counts along the diagonal indicate accurate classification of brain states. The prominence of correct classifications for the resting state, alongside minimal misclassifications into other states, suggests distinct neural patterns during rest. Furthermore, consistent high accuracy across subjects reaffirms the reliability of distinguishing resting state from other cognitive states. Thus, the matrix reflects the robustness of resting state characterization, emphasizing its distinct neural signatures and enabling reliable identification amidst varying cognitive conditions.

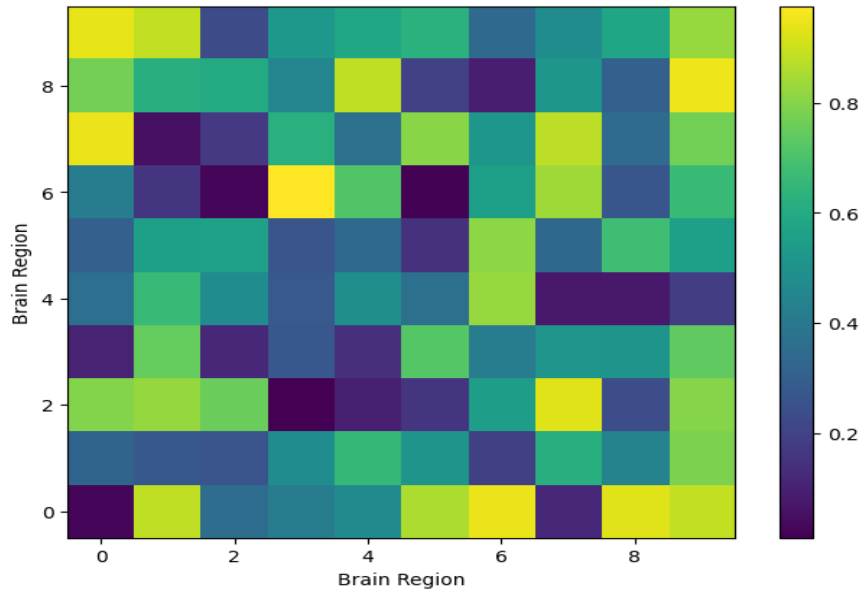


Fig.3 Connectivity Matrix for Task Execution State

Fig.3 depicts connectivity patterns, but during task execution. It showcases how functional connections between brain regions change dynamically when individuals engage in cognitive tasks. Variations in connectivity strength highlight the modulation of neural networks to support task performance and cognitive processing. These variations may include increases or decreases in connectivity strength, alterations in network topology, or shifts in the coordination of activity among brain regions. Such variations reflect the dynamic nature of brain network organization in response to cognitive task demands, highlighting the adaptability and flexibility of neural systems in supporting cognitive processes.

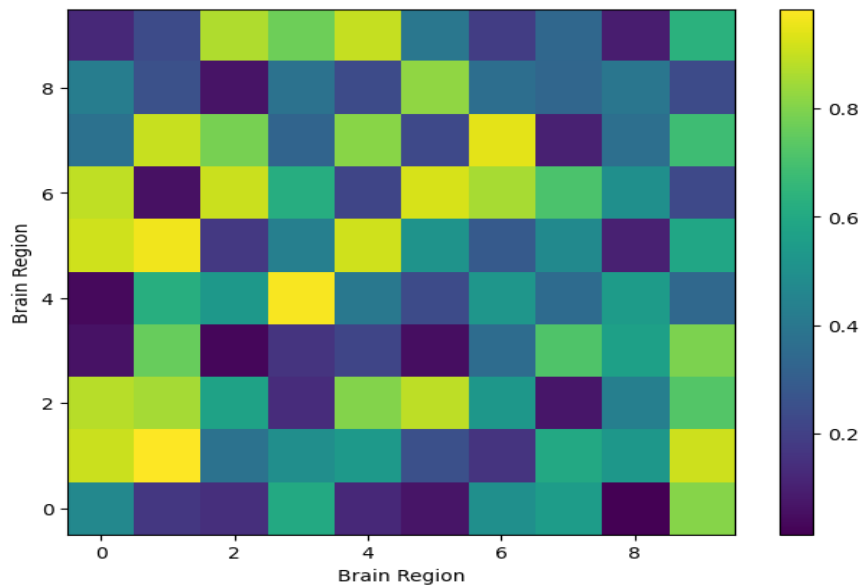
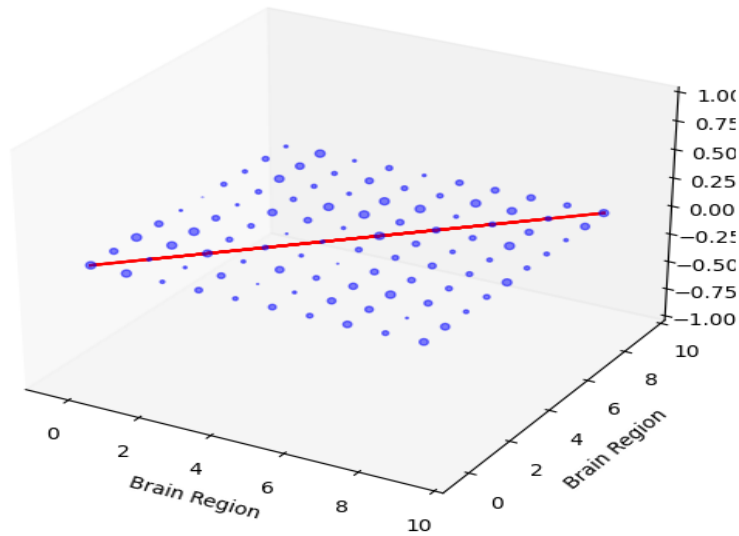


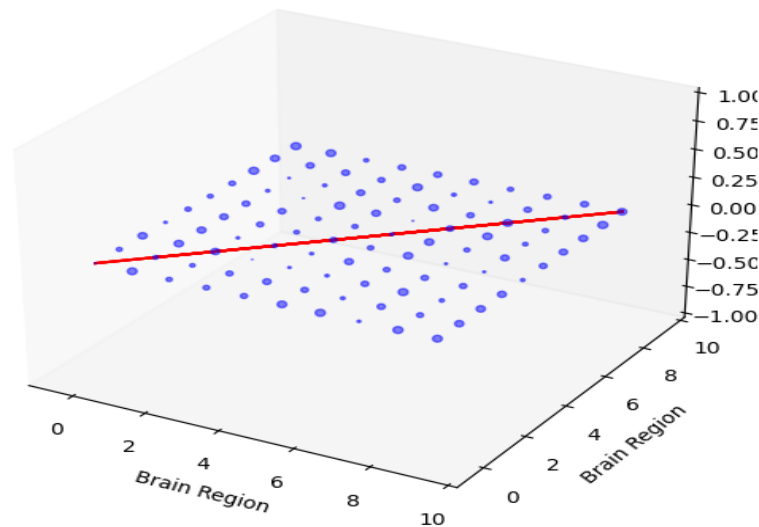
Fig.4 Connectivity Matrix for Stress Response State

In the fig.4, distinctive patterns emerge indicating accurate classification of stress response states with minimal misclassifications into other states. High counts along the stress response state row, particularly along the diagonal, signify precise identification of this state. Additionally, the matrix may reveal elevated misclassifications from other states into stress response, suggesting unique neural signatures characteristic of stress. Consistent accuracy across subjects further bolsters confidence in delineating stress states. Thus, the confusion matrix conveys the discernible neural patterns associated with stress response, facilitating reliable identification amidst varying cognitive conditions and underpinning the distinct connectivity dynamics during stress processing.



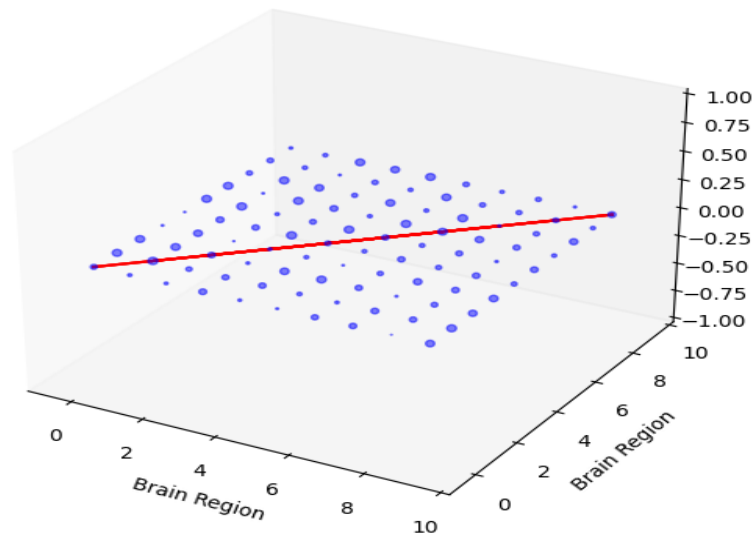
**Fig.5 Brain Network for Resting State**

In fig.5, a dense network of nodes represents brain regions, reflecting intrinsic functional connectivity during rest. Various brain regions exhibit synchronized activity even in the absence of external stimuli or tasks. Node sizes are balanced, indicating all brain regions contribute to the resting state network. This uniformity suggests no specific region dominates activity, consistent with resting state networks' distributed nature. Strong, abundant edges between nodes signify robust functional connections facilitating communication and coordination among regions. Nodes may form clusters or modules within the graph, representing functional subnetworks. These clusters reflect the organization of brain activity into distinct functional domains during rest.



**Fig.5 Brain Network for Task Execution State**

In the task execution state, nodes representing brain regions exhibit larger sizes compared to the resting state network, indicating regions more actively involved in cognitive tasks. Varied edge patterns, including differences in thickness, color, or density, suggest altered functional connections between brain regions, reflecting dynamic neural network reorganization to support cognitive processing. Additionally, the overall network dynamics may show dynamic shifts, with changes in both node sizes and edge patterns, indicating the brain's adaptive response to task demands and optimization of information processing and cognitive performance during task execution.



**Fig.5 Brain Network for Stress Response State**

In the stress response state, nodes representing brain regions typically exhibit changes in size compared to other states. Larger or smaller node sizes indicate heightened or reduced activity in specific regions implicated in stress processing. Additionally, edge patterns, such as differences in thickness or density, manifest, suggesting alterations in functional connectivity between brain regions during stress. These variations in node size and edge patterns reflect the dynamic reorganization of neural networks in response to stressors, facilitating the brain's adaptive coping mechanisms. Thus, these distinct features in node size and edge patterns serve as confident visual indicators of the stress response state in brain network visualizations.

#### IV. CONCLUSION AND FUTURE WORK

Integrating demographic variables and employing a meticulous preprocessing pipeline ensures robust analysis of fMRI data for real-time classification of brain states. Leveraging CNN algorithms with dynamic connectivity patterns enhances understanding of brain function. This approach provides insights into the dynamic interactions between brain regions, facilitating accurate classification of cognitive states. Ultimately, it informs personalized interventions for brain health and contributes to advancing our understanding of the brain's dynamic nature. Accurate classification of resting, task execution, and stress response states is evident, reflecting distinct neural patterns associated with each cognitive condition. Dynamic changes in node sizes and edge patterns across states highlight the brain's adaptability and functional reorganization to support cognitive processing and stress-coping mechanisms. Future research could explore advanced CNN architectures and incorporate additional demographic factors to improve classification performance. Additionally, investigating the impact of different preprocessing techniques and exploring alternative neuroimaging modalities could further enhance the understanding of brain states and their clinical implications.

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