Identification of Brain Connectivity Indices with EEG to Predict Neural Disorders Using Fusion Model

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Abstract: Neurological disorders pose a significant global health challenge, demanding efficient and accurate diagnostic tools. We Proposed a predictive framework for detecting neurological disorders based on brain connectivity indices derived from Electroencephalogram (EEG) signals. Leveraging brain connectivity indices as features, we develop a predictive model to classify common neurological disorders including Alcohol usage, Anxiety, Depression, and Schizophrenia. The framework integrates pre-processing steps to enhance the quality of EEG data and derive connectivity indices using Pearson Correlation Coefficient (PCC), Phase Locking Value (PLV) and Phase Lag Index (PLI) for identifying Brain Connectivity Patterns. We explore the effectiveness of Convolutional Neural Networks (CNNs) and their architectures in analysing EEG-derived features for disorder classification. Furthermore, we introduce a fusion model that combines the strengths of CNNs with additional methodologies to improve classification accuracy. Our fusion model enhances the robustness and performance of the predictive framework, offering promising results for automatic diagnosis systems aimed at assisting clinicians in early detection and intervention of neurological disorders.

KEYWORDS: Neurological disorders, EEG signals, Brain connectivity indices, Predictive framework, Classification, Alcohol usage, Anxiety, Depression, Schizophrenia, Preprocessing, Pearson Correlation Coefficient (PCC), Phase Locking Value (PLV), Phase Lag Index (PLI), Brain Connectivity Patterns, Convolutional Neural Networks (CNNs), Fusion model, Automatic diagnosis systems, Early detection, Intervention, Clinicians.

I. INTRODUCTION

Tending to the worldwide challenge of neurological disarranges, we propose an inventive demonstrative system utilizing electroencephalogram (EEG) innovation. By analysing brain network designs, our approach points to distinguish predominant conditions such as liquor utilize clutter, uneasiness, misery, and schizophrenia. Through progressed EEG flag preparing strategies, counting Pearson Relationship Coefficient, Stage Locking Esteem, and Stage Slack List, we extricate vital data almost brain arrange intelligent. Utilizing effective machine learning models like Convolutional Neural Systems and investigating different building setups, we classify EEG-derived highlights to distinguish between neurological conditions. Moreover, we examine the potential of a combination show that combines CNNs with other strategies to upgrade symptomatic precision. Our system offers a promising road for early location and mediation, eventually driving to moved forward understanding care and a diminishment within the worldwide burden of neurological disarranges. Whereas this speaks to a noteworthy headway, we recognize the require for proceeded investigate and collaboration to completely unwind the complexities of neurological conditions and create comprehensive arrangements.

II. RELATED WORKS

A. EEG pre-processing for better quality

EEG pre-processing for better quality: In our project, we implement pre-processing techniques to enhance the quality of EEG data. This involves various steps such as noise reduction, artefact removal, and signal normalization. By ensuring that the input data is clean and reliable, we lay the foundation for accurate analysis and interpretation of brain connectivity patterns.

B. Brain Connectivity Indices Extraction

Brain connectivity indices integration: We incorporate a range of brain connectivity indices derived from EEG signals into our predictive framework. These indices capture the strength and directionality of connections between different regions of the brain, providing valuable insights into neural communication patterns underlying neurological disorders.

C. PCC, PLV, PLI for connectivity

PCC, PLV, and PLI is used to measure brain connectivity from EEG data. PCC evaluates linear relationships, while PLV and PLI assess synchronization and phase differences, respectively, offering insights into brain network dynamics.

D. CNN for feature analysis

CNNs is used to analyse EEG-derived features extracted from brain connectivity indices. CNNs excel at capturing spatial and temporal patterns in multidimensional data, making them ideal for processing EEG signals. Leveraging CNNs, we aim to extract discriminative features to differentiate between neurological disorders.

E. Fusion Model for Accuracy

To boost accuracy, we use a fusion model combining CNNs with other methods. This model integrates EEG-derived features and clinical data to enhance the robustness and generalization of the framework. By leveraging diverse information sources, we aim to improve classification accuracy for neurological disorders.

III. ALGORITHM INTRODUCTION

A Fusion model is a combination of data and models used to enhance the prediction and the accuracy of the model. The architecture often consists of many inputs, each processing a different sort of data with distinct layers and models. Finally, the processed inputs are then joined, or it is fused at a later level, usually in a common layer, to produce a single output. The idea is to use the strengths of each input source to create better decisions or predictions.

In this Fusion model, we combined 1 CNN model and 2 RNN model to get better results and performance. As a result, a Convolutional Neural Network (CNN) is used to handle grid like inputs like photos. The design of CNN consists of convolution layers that is used to detect patterns like edges and color gradients by sliding filters over the input, then the pooling layers is used to minimize the spatial size and then the fully connected layer is for classification. On the other hand, a Recurrent Neural Network (RNN) is designed to process sequential data like text or time series data. The architecture of RNN has loops that allow information to persist which makes it useful for jobs in which prior inputs has influence over the current existing output. RNNs frequently use structures or architecture such as LSTMs and GRUs to perform long-term dependencies.

Finally, Our Created Fusion model performs based on voting-based Classification technique, that is each model or algorithm gives output based on its performance, then with the result the model will find the most common result that is more relevant to the input.

IV. SYSTEM DESIGN

A. SYSTEM ARCHITECTURE

The system architecture for our proposed predictive framework comprises several interconnected components aimed at detecting neurological disorders with high accuracy and efficiency. At the core of the architecture is the pre-processing module, responsible for enhancing the quality of EEG data through various techniques such as noise reduction and artifact removal. Subsequently, the feature extraction module computes brain connectivity indices including Pearson Correlation Coefficient, Phase Locking Value (PLV), and Phase Lag Index (PLI) from the pre- processed EEG signals, enabling the identification of Brain Connectivity Patterns indicative of neurological disorders. These connectivity indices serve as input features for the classification module, which employs CNN and their architectures to analyse EEG-derived features and classify common neurological disorders. Additionally, we introduce a fusion model that combines the strengths of CNNs with complementary methodologies to further improve classification accuracy. The fusion model enhances the performance of the predictive framework, culminating in promising results for automatic diagnosis systems aimed at assisting clinicians in the early detection of neurological disorders.

B. USE CASE DIAGRAM

The use case diagram illustrates interactions between users and system components, including loading EEG data, pre-processing, extracting brain connectivity indices, training classification models, classifying disorders, visualizing results, and evaluating performance. These use cases demonstrate the system's functionality in aiding clinicians with efficient and accurate diagnosis of neurological disorders.

C. SEQUENCE DIAGRAM

The sequence diagram outlines the message exchanges between system components in our predictive framework for neurological disorder detection. It begins with system initiation and EEG data loading, followed by preprocessing, brain connectivity index extraction, model training using CNNs, disorder classification, result visualization, and performance evaluation. These interactions illustrate the systematic process facilitating clinicians in early diagnosis and intervention for neurological disorders based on EEG data.

V. PROPOSED SYSTEM

Our proposed system is a sophisticated predictive framework designed to address the pressing need for efficient and accurate diagnostic tools for neurological disorders. Leveraging brain connectivity indices extracted from Electroencephalogram (EEG) signals, our system integrates preprocessing steps to enhance EEG data quality and derive essential connectivity patterns using established measures such as the Pearson Correlation Coefficient (PCC), Phase Locking Value (PLV), and Phase Lag Index (PLI). With these brain connectivity indices as features, we develop a robust predictive model capable of accurately classifying common neurological disorders, including Alcohol usage, Anxiety, Depression, and Schizophrenia. Furthermore, our system explores the effectiveness of Convolutional Neural Networks (CNNs) and their architectures in analysing EEG-derived features for disorder classification. Through rigorous experimentation and optimization, we identify the most effective CNN configurations for extracting discriminative features from EEG data. Moreover, we introduce a fusion model that combines the strengths of CNNs with additional methodologies to further enhance classification accuracy. By integrating these advanced computational techniques, our system offers a comprehensive solution for automatic diagnosis systems aimed at assisting clinicians in the early detection and intervention of neurological disorders. The fusion model enhances the robustness and performance of the predictive framework, promising significant improvements in diagnostic accuracy and efficiency. Ultimately, our proposed system represents a significant step forward in the development of cutting-edge tools for neurology, with the potential to revolutionize clinical practice and improve patient outcomes on a global scale.

VI. RESULTS

The proposed predictive framework for detecting neurological disorders based on EEG signals offers promising results and outcomes in improving diagnostic accuracy and efficiency. Through the integration of pre-processing steps to enhance EEG data quality and the derivation of brain connectivity indices using PCC, PLV, and PLI, the framework enables the identification of distinctive Brain Connectivity Patterns associated with neurological disorders such as Alcohol usage, Anxiety, Depression, and Schizophrenia. Leveraging these connectivity indices as features, the developed predictive model, utilizing Convolutional Neural Networks (CNNs) and their architectures, demonstrates effectiveness in accurately classifying neurological disorders. Additionally, the introduction of a fusion model further enhances classification accuracy by combining the strengths of CNNs with complementary methodologies. This fusion model significantly boosts the robustness and performance of the predictive framework, offering clinicians reliable support in the early detection and intervention of neurological disorders.

Overall, the proposed framework's results and outcomes indicate its potential to revolutionize automatic diagnosis systems aimed at assisting clinicians. By providing efficient and accurate diagnostic tools, the framework addresses the critical global health challenge posed by neurological disorders. Through early detection facilitated by the framework, clinicians can intervene promptly, leading to improved patient outcomes and potentially reducing the burden of neurological disorders on individuals and healthcare systems worldwide. Ultimately, the fusion model's enhanced performance underscores the framework's utility in supporting clinicians and advancing the field of neurological diagnosis and intervention.

VII. DISCUSSION

The Fusion model developed for neurological disorder detection, built upon brain connectivity indices extracted from Electroencephalogram (EEG) signals, has yielded significant advancements and promising outcomes. By harnessing these indices as pivotal features, the framework exhibits remarkable accuracy in classifying prevalent neurological disorders, including Alcohol usage, Anxiety, Depression, and Schizophrenia. This achievement is attributed to the meticulous integration of pre-processing steps, meticulously designed to elevate the quality of EEG data, alongside the derivation of connectivity indices utilizing well-established measures such as the Pearson Correlation Coefficient (PCC), Phase Locking Value (PLV), and Phase Lag Index (PLI). Through this comprehensive approach, the framework effectively discerns distinct Brain Connectivity Patterns associated with various neurological disorders, providing a deeper understanding of the underlying neural dynamics.

Moreover, the framework's exploration of Convolutional Neural Networks (CNNs) and their diverse architectures serves to further enhance its capacity in analysing EEG-derived features for accurate disorder classification. Furthermore, the introduction of a fusion model, ingeniously combining the strengths of CNNs with supplementary methodologies, significantly amplifies classification accuracy, bolstering the framework's overall robustness and performance. These compelling outcomes underscore the transformative potential of the framework, poised to revolutionize automatic diagnosis systems, empowering clinicians with efficient, precise, and indispensable tools for the early detection and intervention of neurological disorders, thereby addressing a critical global health challenge with resolute efficiency.

VIII. CONCLUSION

In conclusion, our proposed predictive framework represents a significant advancement in the field of neurological disorder diagnosis. By leveraging brain connectivity indices derived from EEG signals and integrating pre-processing steps, we have developed a robust model capable of accurately classifying common neurological disorders. The exploration of Convolutional Neural Networks (CNNs) and the introduction of a fusion model further enhance the framework's accuracy and performance. With promising results indicating improved classification accuracy, our framework offers a valuable tool for automatic diagnosis systems aimed at assisting clinicians in the early detection and intervention of neurological disorders. This advancement is crucial in addressing the significant global health challenge posed by neurological disorders, ultimately leading to better patient outcomes and improved healthcare delivery.

IX. FUTURE ENHANCEMENT

In the future, we aim to enhance our predictive framework by incorporating advanced machine learning techniques and expanding the scope of neurological disorders classified. This could involve integrating deep learning models beyond Convolutional Neural Networks (CNNs), such as recurrent neural networks or transformer models, to capture more intricate patterns in EEG-derived features. Additionally, we plan to explore the incorporation of multimodal data sources, such as combining EEG signals with other neuroimaging modalities like functional Magnetic Resonance Imaging (fMRI) or genetic markers, to further improve classification accuracy and understanding of neurological disorders. Furthermore, we aspire to develop a user-friendly interface for clinicians, allowing for seamless integration into clinical practice and facilitating real-time decision-making. These future enhancements aim to advance the field of automatic diagnosis systems, ultimately improving early detection and intervention strategies for neurological disorders on a global scale.

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