Deep learning Approach to Classify Cognitive Workload using Functional Connectivity Features

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Abstract

The cognitive workload plays a critical role in tasks that require dynamic decision-making and are conducted under high-risk, real-time conditions. A high workload might result in unforeseen and disproportionate dangers, whereas the result of a low workload is disengagement from the activity. This emphasizes the significance of maintaining adequate cognitive effort in high-risk settings to complete the task successfully. In this study, we employ several functional connectivity measurements in conjunction with deep learning to categorize cognitive workload. This study makes use of an N-back EEG dataset. Following pre-processing, functional connectivity features such as phase locking value (PLV), phase lagging index (PLI), and coherency were extracted. These characteristics are directed/non-directed, allowing for speedier calculations. The deep learning classifier CNN utilizes these features to classify the cognitive workload into three categories: low (0-back), medium (2-back), and high (3-back).we achieve the highest accuracy of 93.75 % using PLV in CNN-A architecture, 87.5% accuracy by using Coherency in CNN-A Architecture, and 68.75% using PLI in CNN-A architecture. By leveraging deep learning methods to analyze functional connectivity features, this research opens avenues for understanding and supporting cognitive processes in various domains, including robotics, healthcare, and education. The scope of the study could be extended to explore the possibility of categorizing cognitive effort in complex, real-world situations that occur in real time and involve dynamic and intricate circumstances.

Keywords: EEG, Functional Connectivity, Cognitive workload, CNN

1. Introduction

The term "Cognitive Workload" refers to the mental effort needed to do any task appropriately. Working memory is responsible for processing information briefly, while long-term memory is involved in storing information for extended periods. Effectively utilizing working memory is crucial for tasks such as math operations, reading, and learning. Cognitive workload refers to the mental effort required by working memory to successfully accomplish any given task. In today`s world, everyone is surrounded by sensory information. Sensory memory accepts the data and tries to filter out most of the information and also keeps an impression of the most important items long enough for them to pass into working memory. Your working memory receives information from your sensory memory, which will process or discard according to need. At a certain time, working memory can typically store Five to nine items (or chunks of information). As we see it is important for Cognitive Load Theory that when information is processed by the brain, information is categorized accordingly and moved into long-term memory, where it will store in knowledge structures known as "Schemas". The categorized data is based on how you intend to use it. So, for instance, there are schemas for the concepts of a dog, a cat, a mammal, and an animal.

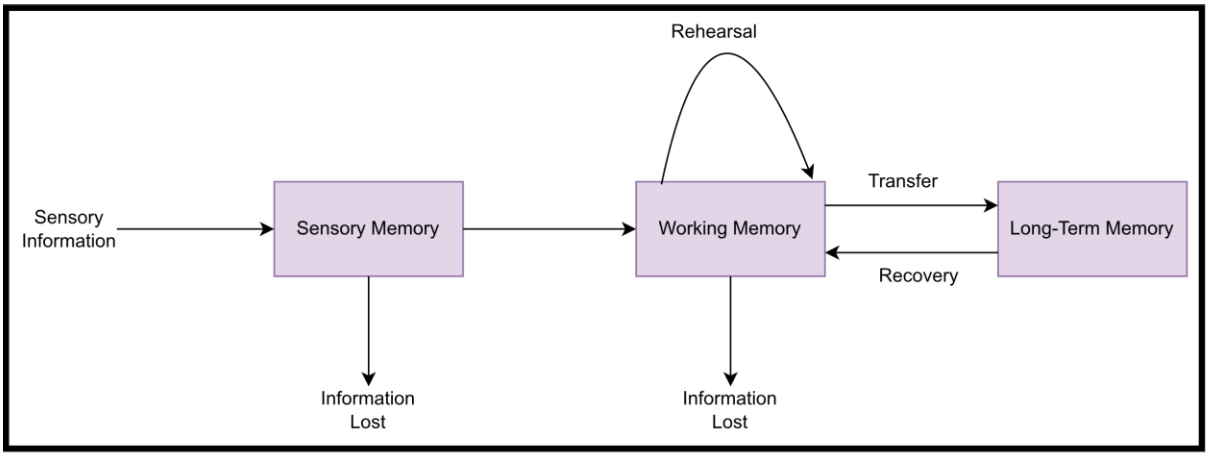


Fig 1: Information Processing Model

In tasks that involve human-machine collaboration, evaluating an individual's cognitive workload is essential. The workload experienced by an individual during any task is influenced by the speed at which information is processed. A high workload might result in unforeseen and disproportionate dangers, whereas the result of a low workload is disengagement from the activity. This underscores the importance of maintaining an optimal cognitive workload in high-risk settings to effectively accomplish tasks. Emotional intelligence and stability are considered vital factors that contribute to cognitive workload. Several studies have found a link between emotional quotient and certain cognitive skills. As a result, cognitive workload categorization can be an important sign of emotional quotient and reliability.

This paper aims to categorize cognitive load into three classes medium, low, and high by using functional connectivity features extracted from EEG single and deep learning models. In this paper, we selected three functional connectivity features Phase locking value (PLV), Imaginary part of Coherency, and phase lagging index to plot a connectivity graph that will act as an input for our CNN models. The dataset used in this is readily available in [19-20] and the dataset description is also mentioned in the cited paper. We use the n-back dataset for this task as the cognitive load on persons increases as value 'n' increases i.e., a person needs to remember the previous n^{th} element to complete the given task. After the training of CNN models, performance analysis is performed to select the best combination to determine the cognitive workload.

2. Literature Review

Cognitive simply means the mental ability of a person who is required to perform any tasks like arithmetic, playing soccer, coding, etc. Cognitive workload signifies the amount of working memory being used at a time. If working memory gets fully occupied, a person's thinking and decision-making ability get drastically affected.

Although we know that cognitive workload measuring is a very important process, but not an easy one. At first, the researchers try using subjective measures like interviews, questionnaires, and quiz-based approaches where participants have to self-report their mental states for the evaluation of their cognitive load. But there are some issues with this type of approach It is a self-assessment of a person meaning these methods are subjective to an individual participant which leads to unreliable, biased, unique, and coherent metrics for evaluation. The other disadvantage can be that it cannot provide real-time analysis of cognitive load as the data is based on post-task questionnaires. This type of study is conducted by groups of research such as [1] and [2], a study done by the Subjective Workload Assessment Test (SWAT)

As questionnaires-based approaches are subjective and unable to produce real-time data, it is a hindrance in the research of brain-related activities such as cognitive workload. To make cognitive analysis generalized and accurate these techniques should be used 1) invasive method means invading the body by the means of cutting, inserting instruments, and puncturing the skin. 2) non-invasive method does not require any breaking or rupturing of skin, due to which this type of method is favorable in the area of brain analysis. Neurophysiologic signals are a type of non-invasive method allowing the real-time analysis of cognitive load. BCI (Brain Computer Interface) has come a long way since its start in the 1960s. BCI has created several assistive and rehabilitative using brain imaging methods [3]. Examples of brain imaging methods can be classified based on their signal acquisition as electroencephalogram (EEG) is an electrical type, functional magnetic resonance imaging (fMRI) [4] is a magnetic type, NIRS (Near-infrared spectroscopy) is related to the oxygen concentration in blood, etc. EEG is a low-cost, non-invasive, and passive recording technique, the first time it is used on humans in the 1920s. EEG has many advantages over other brain imaging techniques it`s cost is low as compared to fMRI, and have high temporal resolution i.e. it collects thousands of snapshots of electrical signal in a second from multiple electrodes simultaneously (i.e. sampling rate is very high) unlike fNIRS with very low sampling rate. And the implementation or data collection process is very easy, as the electrodes are mounted on the elastic cap to insure accurate data collection from the same scalp. Due to this EEG becomes an excellent technology for studying the time series of cognitive functions. EEG Electrical impulse is so tiny, that it needs to be passed by an amplifier to make data useful for the time-series analysis.

The EEG has become the highly accepted measure for the real-time analysis of cognitive workload [5-7]. There are various EEG features for the assessment of different brain-related activities. Frequency, time, spatial, and time-frequency domain characteristics are collected from the raw EEG to analyze EEG signals. Statistical characteristics, Event-Related Response [8], Hjorth parameter, and the higher order crossing analysis [9], are the common time domain features. Frequency domain feature such as frequency decomposition into sub-bands used in the study related to deep sleep drowsiness, and relaxed, engaged, aware, and active states [10]. These features are used for determining by employing machine learning techniques. Motamedi-Fakhr et al. [11] presented an overview of more than 15 commonly used methods and features for human sleep analysis (e.g., coherence analysis, wavelet transform, Hjorth parameters, and short-time Fourier transform). Aside from these characteristics, they also evaluated research publications on sleep stage categorization. Rashid et al. [12] discussed the difficulties in the present state of the art and potential solutions. They also briefly covered the significant often utilized characteristics for BCI, which are classed as Frequency, time, spatial, and time-frequency domain

In the past, studies on cognitive load estimations were done but they do not employ the use of EEG data with machine learning and deep learning [34-45]. If they do make use of ML and DL, they limit their study to the binary categorization of cognitive load into low and high by extracting computationally intensive EEG characteristics from raw data, which is unsuitable for real-time or real-life settings.

Zhang et al. [13], the authors utilized CNN and RNN models to achieve the binary classification of workload using EEG topographic maps, achieving 88.9% accuracy. Building upon this approach, another research [14] extended the classification task to three classes of cognitive workload using the same topographic maps as input for a CNN model, achieving a higher accuracy of 91.9%.

EEG data provides the resulting perception of the brain by capturing the activity originating from specific brain regions, revealing interregional connectivity, and shedding light on the level of activity in different brain areas during various tasks. This enables researchers to explore important characteristics related to specific cognitive states [25-33]. However, comprehending neural activities remains a complex endeavour, highlighting the importance of investigating the connections among different brain regions, known as brain connectivity. Functional connectivity, a component of brain connectivity, exhibits a strong correlation with cognitive load, further emphasizing its significance in understanding cognitive processes.

Dimitrakopoulos, et al. [15] uses n-back and mental arithmetic dataset for binary classification of cognitive load using SVM and can achieve an accuracy of about 88% for N-back and 87% cross-task.

Shau Yang et al. [24] have proposed a novel method to assess cognitive mental workload (MW) using EEG signals by leveraging deep learning techniques. The key idea is to incorporate a feature mapping layer into a stacked denoising autoencoder (SDAE) to effectively capture personalized properties in the high-dimensional EEG indicators. This feature mapping layer proves to be efficient in preserving local information within the EEG dynamics. To further enhance the classification accuracy, the shallow hidden layer of the SDAE is redesigned as a feature mapping layer, which also ensures the preservation of local information in EEG dynamics. This modification enables the extraction of individual-specific properties from the EEG data, which are then fused to accurately reflect the cognitive MW levels. The resulting framework, named Ensemble SDAE Classifier with Local Information Preservation (EL-SDAE), demonstrates impressive performance. It achieves an outstanding accuracy of 92% in subject-average classification, outperforming various classical shallow and deep classifiers. Overall, the introduction of the feature mapping layer in the SDAE architecture, along with the fusion of individual-specific properties, contributes to the high performance of the EL-SDAE in cognitive mental workload classification.

Zarjam, et al.[22] use an arithmetic task dataset and wavelet entropy-based EEG features with ANN model to achieve 98.44% of accuracy on subject-independent multi-class classification into 7 classes of cognitive workload.

Mingkan Shen et al. [23] use functional connectivity features from EEG with 3D-CNN deep learning models to identify Schizophrenia which is a devastating mental disorder of the human brain that causes a serious impact on emotional inclinations, quality of personal and social life, and the healthcare systems with 97.74% of accuracy. Functional connectivity is calculated through the mutual information algorithm. He also compared the connectivity features in the support vector machine and multilayer perceptron and received 90.16 % and 92.08%.

Some of the functional connectivity features like PLV contain the problem of volume conduction which can produce inaccurate EEG data during acquisition. Volume conduction can be described as the recording of electrical potential originating from a distant source with a phase difference of 0 or π. So, to address the problem of volume conduction in the assessment of functional connectivity, Cornelis J. Stam, et al. [16] propose a phase synchronization quantification method and establish the performance comparison with imaginary coherency and phase coherence.

Anmol Gupta, et al. [17] uses EEG-based connectivity features with deep learning models and achieves 97.92% accuracy on the subject-specific based multiclass classification of high, low, and medium cognitive workload. PLV, MI, and PTE are connectivity features used with different combinations of DL models CNN-LSTM, LSTM, and CNN for classification and the best result is achieved using CNN with PLV and combination results are such as MI+CNN at 80.87%, MI+LSTM at 71.87% and MI+CNN at 95.83%.

3. Proposed Model

The architecture that was used is depicted in Fig 2 below. The raw electroencephalography (EEG) data is fed into the EEG processing pipeline. The raw data files are loaded into memory as the first step. There are numerous file formats for storing EEG data for example BrainVision uses an EEG/VHDR/VMRK file triplet to store data, BioSemi amplifiers use BDF files (an extension of the European Data Format), Neuroscan amplifiers use proprietary CNT files, and so on.

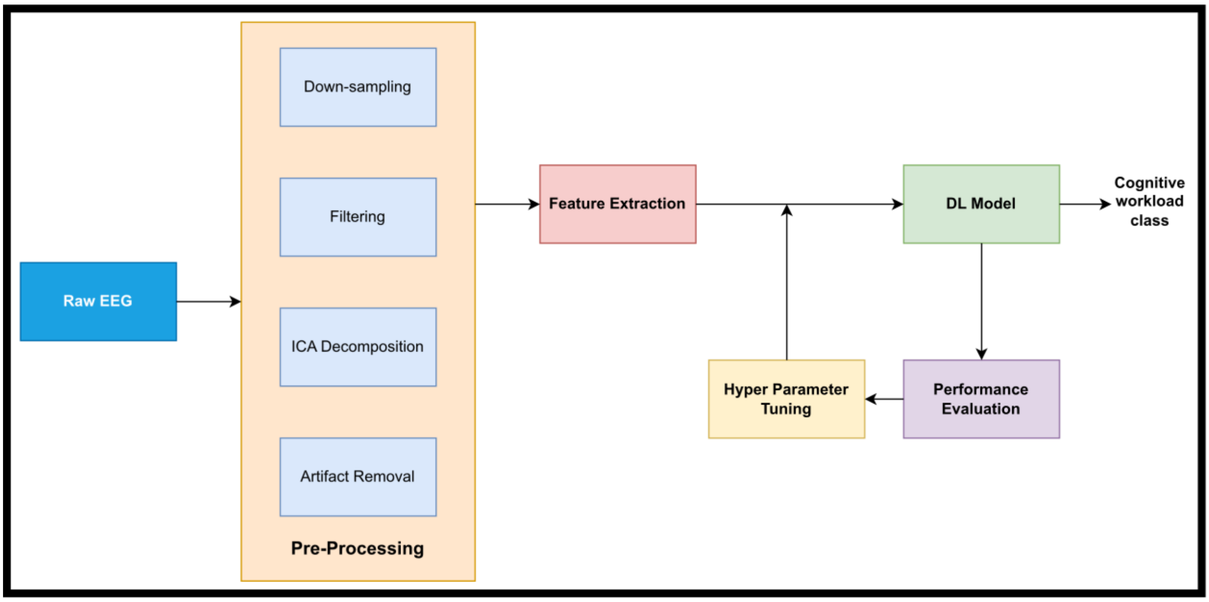


Fig 2 Architecture

The architecture can be broadly divided into three parts:

1. Pre-processing

2. Feature Extraction

3. Implementation of Deep Learning Model

3.1 Pre-processing

Pre-processing is a crucial step in converting raw data into a more suitable format for further analysis, enhancing interpretability, and gaining an extreme acknowledgment of the underlying neural signals. In this study, the MNE package in Python was utilized for pre-processing purposes.

During pre-processing, it`s important to consider that spatial information may be lost in the signals obtained from the brain, leading to potential inaccuracies in representing the true neural signals.

Additionally, EEG data often contains various sources of noise, which can mask weaker EEG signals of interest. Artifacts such as blinking and muscle movement further contribute to data contamination and distortion.

To tackle these obstacles, one common practice is to apply frequency integration and filtering techniques to the digital signal, whether it is audio, EEG, or another type. These techniques selectively remove certain frequencies or retain specific filters to refine the signal and enhance the quality of subsequent analysis

3.1.1 Down-sampling

The provided EEG data had 3 channels and a sample rate of 1000 samples per second (or 1000 Hz = hertz). If each sample is represented as a 32-bit float, the total number of bits per second is (30 * 1000 * 32) = 9,60,000 bits per second.

Down-sampling is a technique for minimizing the number of samples used while retaining the necessary information. The sampling rate was reduced to 256 Hz [17].

After down-sampling, the total number of bits per second is (30 * 256 * 32) = 2,45,760 bits per second.

3.1.2 Filtering

EEG waves are medically established to be divided into several frequency sub-bands, which are delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–80 Hz). The EEG signal, however, is buried beneath the noise.

The application of digital filters is the most common step in the preprocessing of EEG data. Digital filters are a commonly employed tool to enhance the Signal Power to Noise Power Ratio of a signal by reducing the influence of undesired frequencies that are considered noise. For instance, they can effectively suppress unwanted components such as low-frequency skin potentials, high-frequency electromyographic activity, and line noise at 50/60 Hz. By applying digital filtering techniques, the signal's quality and clarity can be improved, making it easier to derive meaningful insights from the data while minimizing the impact of unwanted disturbances. For cognitive workload calculation,4-30Hz of bands are needed. So to remove unnecessary data and noise Band-Pass filter is applied in the range of 0.2Hz and 45Hz [22]

3.1.3 Artifact (Ocular Artifact) Removal

Artifact removal is a crucial step in EEG signal processing to eliminate unwanted signals that can distort or contaminate the EEG data. One common type of artifact is an ocular artifact that is caused by horizontal, and vertical eye movements and blinking.

Ocular artifacts can significantly affect the accuracy and interpretation of EEG data, as they introduce noise and interference that can mask or distort the underlying brain activity. Therefore, the effective removal of ocular artifacts is essential to ensure the integrity and reliability of EEG data analysis.

Various methods can be employed to eliminate ocular artifacts from EEG signals. One common approach is the use of independent component analysis (ICA), which separates the mixed signals into independent components, allowing the identification and removal of components related to ocular artifacts. Another approach is to use regression techniques, where regression models are trained to predict ocular artifacts based on auxiliary channels, such as electrooculogram (EOG) channels. The predicted ocular artifacts are then eliminated from the original EEG signals to remove the artifact contamination.

In addition to these techniques, advanced signal processing algorithms, such as adaptive filtering and wavelet-based methods, can also be utilized to effectively detect and eliminate ocular artifacts from EEG data.

By appropriately removing ocular artifacts, researchers can obtain cleaner and more reliable EEG signals, facilitating accurate analysis and interpretation of the underlying brain activity.

3.1.4 ICA Decomposition

Ocular artifacts were removed using Independent Component Analysis (ICA). EEG data is made up of electrical potentials that come from different sources. Each source (including eye movements and blink artifacts) projects its topography onto the scalp maps.

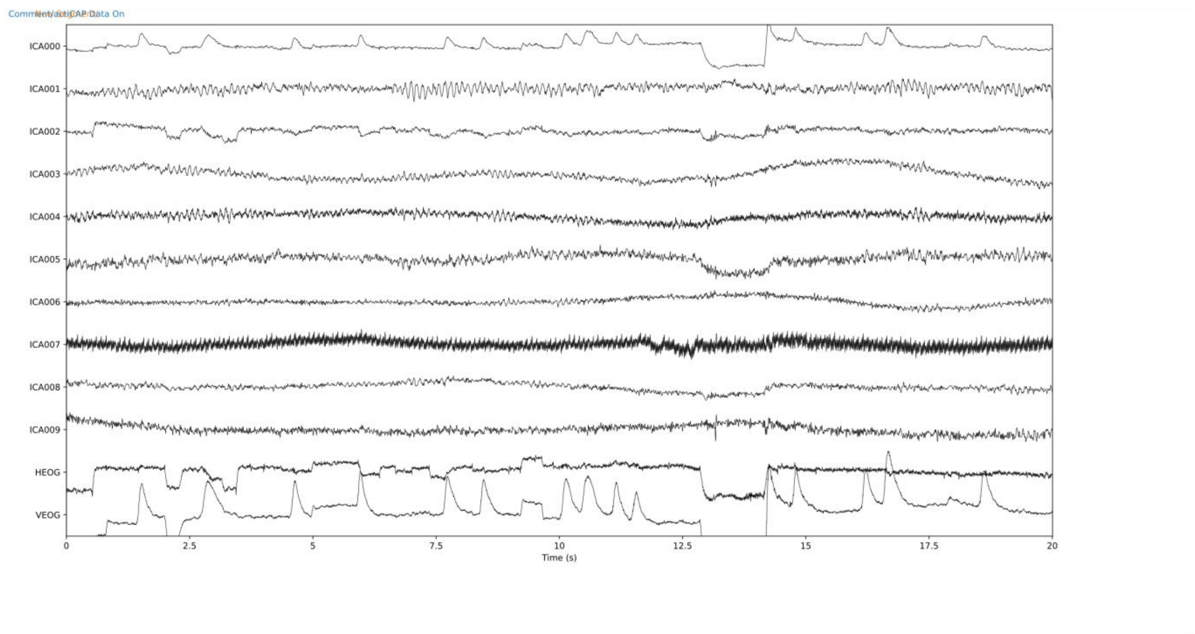


Fig 3 Independent Component Analysis

Fig 3 shows different components of our EEG signals out of which ICA000 and ICA002 are ocular artifacts. ICA is particularly useful in scenarios where the observed signals are a linear combination of unknown source signals, and there is no prior information available about the sources or their mixing process. In the context of EEG analysis, ICA can be used to separate the contributions of different brain sources to the recorded EEG signals. It helps in identifying and isolating specific brain activities or artifacts, enhancing the interpretation and analysis of EEG data.

Utilizing ICA, we were able to explore the individual scalp maps and channels independently, facilitating the exclusion of channels based on their respective regions and levels of activity. This approach provided us with a metric to effectively enhance the data quality through further data cleaning.

3.1.5 Epoch and Event Extraction

EEG epoching is a technique of extracting specific time windows from a continuous EEG signal. These time windows are known as "epochs," and they are typically time-locked for an event, such as a visual stimulus. It could aid in working within specific time constraints and simplifying computations. The different events were then extracted from the loaded event files using their event IDs. This enabled us to examine the events in short time frames and study their occurrence and duration.

In our case, epoch separation is done to extract 0-back,2-back, and 3-back events to do feature extraction on each of the events and then apply a DL model for classification.Fig 4 depicts the occurrence of events in our dataset.

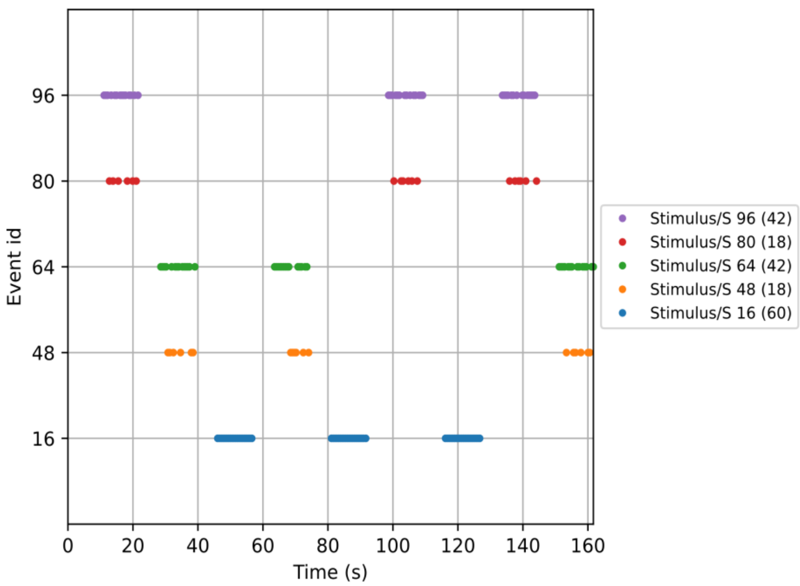


Fig 4: events and their occurrence in one of the subject EEG data

3.2 Feature Extraction

Based on Brodmann's research, specific part of the brain is assigned distinct functions, forming a brain map that delineates these functional areas. During cognitive tasks, different specialized brain regions are activated, and the brain dynamically coordinates the flow of information to accomplish the task. To investigate this dynamic coordination, two methods are commonly employed: oscillation and spike rate analysis. However, this study focus is on exploring dynamic coordination through oscillation rather than spike rate analysis due to anatomical constraints and feasibility limitations. Instead, functional connectivity is utilized as a technique to quantify the association between neurons and analyze the coordination between brain regions. The research incorporates both directed and non-directed model-based approaches to examine functional connectivity, employing measures such as PLI, imaginary coherency, and PLV. These measures facilitate the assessment of integration and relationships among neural signals, delivering valuable insights into the coordination and interactions among different brain regions.

3.2.1 Phase Locking Value (PLV)

PLV is a measuring technique frequently utilized for assessing the synchronization or phase coherence in EEG signals, revealing insights into the consistency of phase relationships over time. It quantifies the degree of phase consistency in EEG signals, offering valuable information about their interrelation.

PLV is calculated by extracting the phase information from the two signals using methods like the Hilbert transform. Let's assume, signals originating from two different regions of the brain or sources can be represented by the Hilbert transform:-

$$z_k = A_k(t)e^{(j\phi k(t))} \tag{1}$$

$$z_l = A_l(t)e^{(j\phi l(t))} \tag{2}$$

The below equation shows the phase difference between the signals at each time point-

$$\Delta\phi_{(k,l)} = \phi_k(t) - \phi_l(t) \tag{3}$$

and the PLV is obtained by averaging these phase differences over a specific time window.

$$PLI = \left| n^{-1} \sum_{n=1}^{n} e^{i(\phi^j - \phi^k)t} \right| \tag{4}$$

A higher PLV indicates stronger phase synchronization between the signals, suggesting that the brain regions associated with those signals are working in a coordinated manner like 1 denotestotal phase synchronization. Conversely, a lower PLV indicates weaker or less consistent phase coupling like 0 reflects no phase synchrony.

3.2.2 Phase lagging index (PLI)

Stam and colleagues [16] introduced PLI to solve the problem of volume conduction with PLV. Volume conduction refers to the phenomenon in which electrical signals generated in the brain spread through the surrounding conductive medium, such as the cerebrospinal fluid and skull, influencing the measurements recorded by electrodes placed on the scalp. It is an important component in the evaluation of electroencephalography (EEG) signals.

When electrical activity occurs in the brain, it generates electric fields that can be measured on the scalp using EEG electrodes. However, these electric fields are influenced by the conductivity and geometry of the surrounding tissues. This leads to the phenomenon of volume conduction, where the electrical signals are propagated and attenuated as they pass through different conductive mediums.

Volume conduction can cause the signals measured at different electrodes to be correlated, even if they are not directly connected. Because the electrical fields generated by brain activity can spread and influence multiple electrodes. As a result, it is important to consider volume conduction effects when interpreting EEG data, as the measured signals may reflect the collective activity of multiple brain regions.

So, the fundamental concept here is to ignore phase locking centered on 0, π, 2π, and so on phase difference to mitigate the effect of volume conduction.

$$PLI = \left| n^{-1} \sum_{n=1}^{n} sgn\left(Im\left[e^{i(\phi^{j}-\phi^{k})t} \right] \right) \right| \qquad (5)$$

In the above equation, sgn denotes the signum function which discards the instantaneous signal phase difference of 0, π, 2 π, 3 π, and so on. The value of PLI lies between 0 to 1 as it is average, where 0 indicates no coupling and 1 indicates no volume conduction is present i.e. true signal. At 0 value volume may or may not present.

PLI calculates the proportion of time points where the phase difference between the signals exceeds a specified threshold, typically set at 0 degrees or π radians. If the difference in the phase distribution is symmetric around the threshold, indicating a lack of consistent phase coupling, the PLI value will be close to 0. Conversely, an asymmetric distribution, with more phase differences consistently above or below the threshold, yields a higher PLI value.

PLI gives information about the strength and presence of phase synchronization between two EEG signals. It is often employed in studies examining functional connectivity and network interactions in the brain, offering insights into how different brain regions communicate and coordinate their activity.

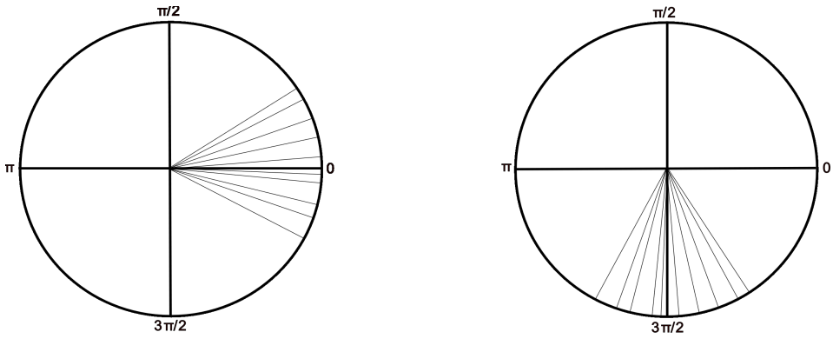


Fig 5

In Figure 5, the left side image shows a 0 value of PLI as differences in the phase distribution are homogeneous around 0. While right side image shows a PLI of 1, as the differences between the phase distributions are 0 and π. of 3π/2.

3.2.3 Imaginary Coherency

The imaginary coherency is a measure used for the analysis of EEG signals to assess the phase relationship between two signals at a specific frequency.

The real and imaginary components of coherency between two-time series can be computed by dividing the cross-spectrum by the square root of the product of the power spectra of the respective signals:

$$c = \frac{\left(A_1 A_2 e^{(i\Delta\phi)}\right)}{\sqrt{A_1^2 A_2^2}} \tag{6}$$

Coherency is a comprehensive measure that integrates both amplitude and phase information in the frequency domain, providing insights into the relationship between two signals.It represents the correlation among the signals at a particular frequency. The imaginary coherency specifically captures the phase relationship between the signals, while the amplitude correlation is represented by the real part of coherency.

Here A1 and A2 represent the amplitudes, and Δϕrepresents the instantaneous phase difference of two times series.

$$Im(c) = \frac{A_1 A_2 \sin \Delta\phi}{\sqrt{A_1^2 A_2^2}} \tag{7}$$

The imaginary coherency quantifies the difference between phases in the signals at the given frequency. In this method, only the imaginary part of coherency is considered, which isolates the phase information while discarding the amplitude information.

According to Nolte et al. [16], the non-zero imaginary part in the coherency measure indicates that the underlying sources of the two-time series are not simply a result of linearly mixed, uncorrelated signals, such as those caused by volume conduction. This suggests that there is an interaction between the sources.

However, it is important to keep in mind that solely relying on the numerical value of the imaginary component is not enough to measure or assess the strength of coupling between the sources. Both the coupling strength and amplitude of the phase difference exert an influence on it.

In summary, the presence of a non-zero imaginary part in the coherency measure allows us to examine the interaction between the underlying sources. However, to ascertain the coupling strength between sources, additional analysis is necessary.

3.3 Deep Learning Model

Deep learning is a sub-domain of machine learning which make use of neural network concepts for model creation and training. It mimics the operations of the human brain to recognize patterns in massive amounts of data, which makes it slightly superior to machine learning [26, 30]. In this research, CNN is used, because our input data is consist of brain connectivity plot images, and CNN is employed for tasks like image classification and object recognition. These models utilize convolutional layers and pooling operations to extract meaningful features from input images automatically. CNNs have demonstrated remarkable performance in various computer vision applications, where they learn and recognize relevant patterns and structures from visual dat. [34-38].

In this research, CNN models are used for the determination of workload and brain connectivity circular plots are used as input images. Two CNN models are used in this research to get better results, both of the models have the same configuration of a convolution layer but have different dense layers. Three convolutions are present with a configuration of 16, 32, and 16 filters each with a kernel size of 3X3 and relu as an activation function, with each convolution layer output going to a max-pooling layer of size 2X2. A dense layer of the first CNN model consists of 2 dense layers, with 256 and 3 neurons with activation functions of relu and softmax respectively. The dense layer of the second model consists of 3 dense layers, with 64,16 and 3 with relu, relu, and softmax activation functions respectively. The last layer of the model consists of 3 neurons because classification needs to be done for 3 classes. And sparse categorical cross-entropy method is used as a loss function.

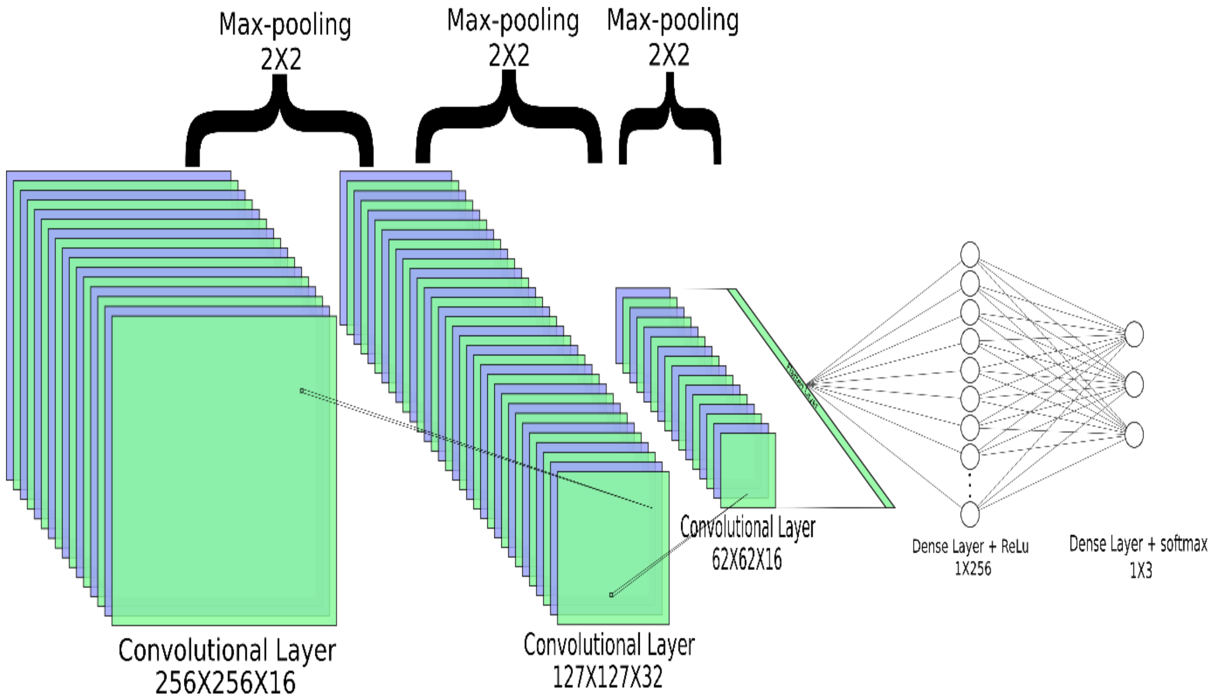


Fig 6(a) CNN-A Architecture

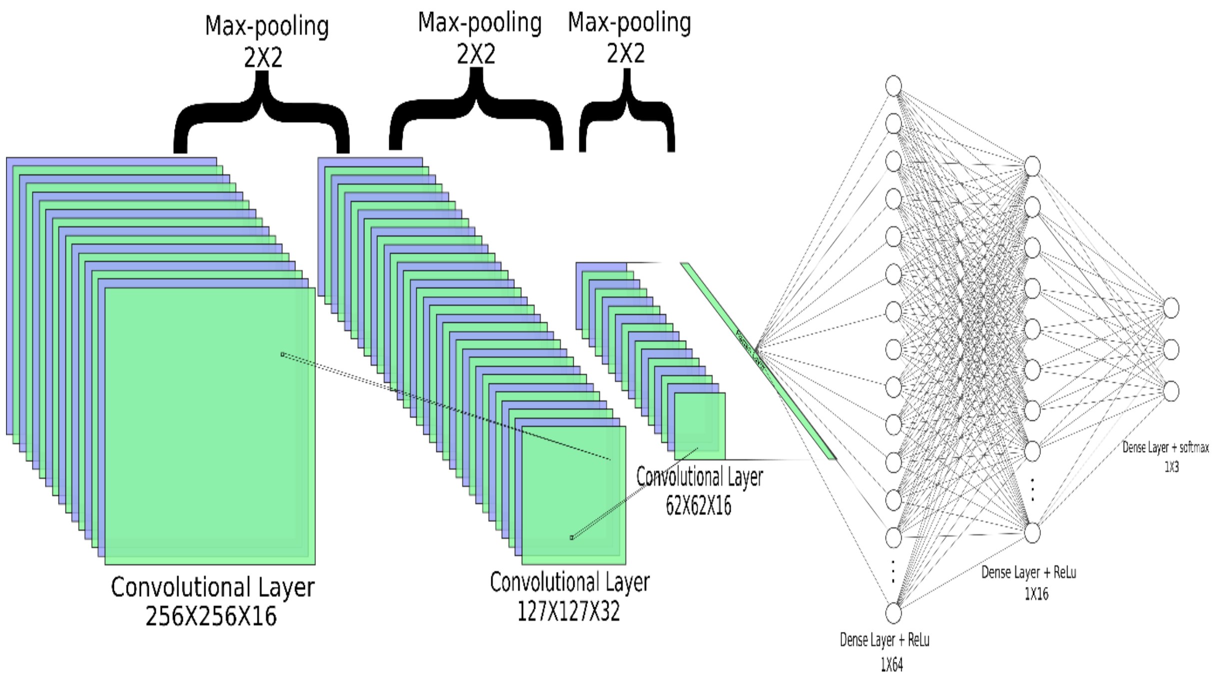
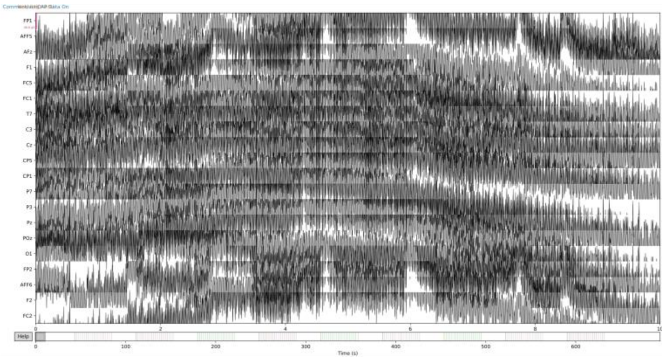


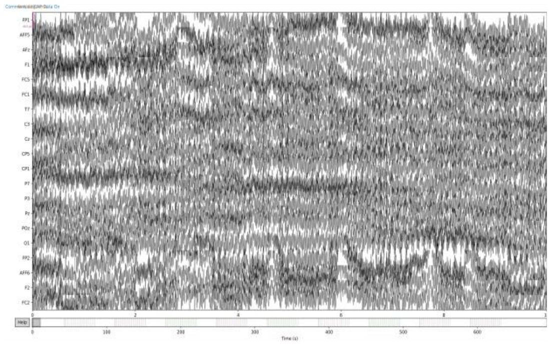
Fig 6(b) CNN-B Architecture

4. Results and Discussion

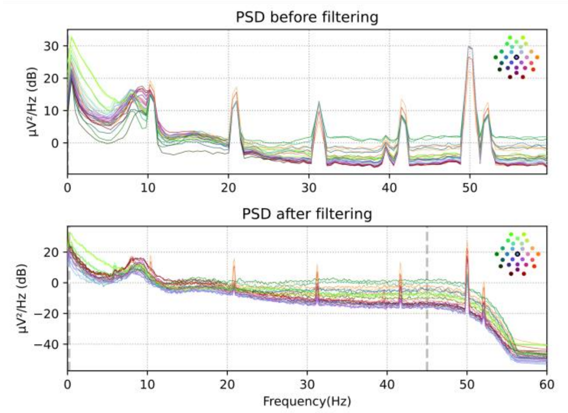
The following findings are obtained using the aforementioned methods, beginning with pre-processing, feature extraction, CNN model performance analysis, and comparison with previous studies.



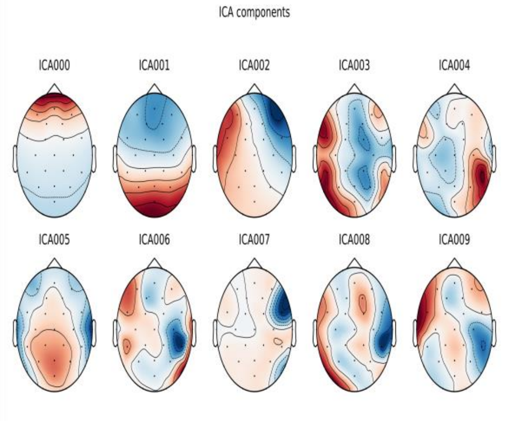
(a) Raw EEG



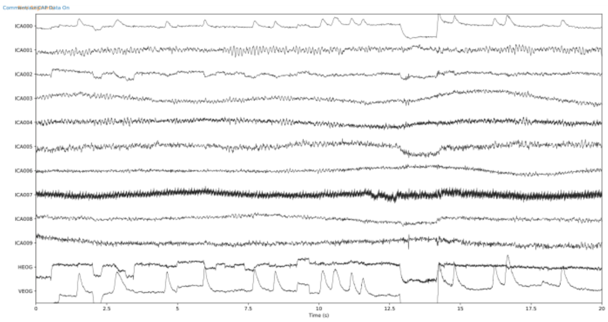
(b) EEG after Filtering



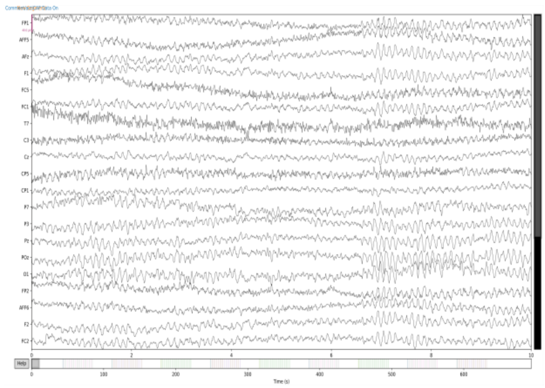
(c) PSD before and after filtering



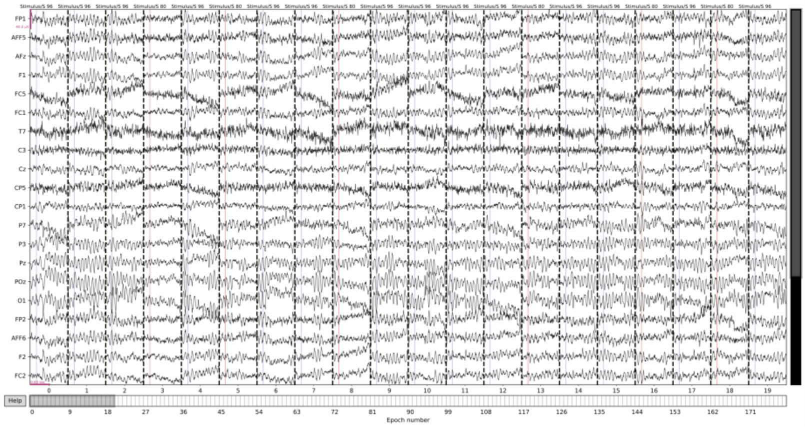
(d) ICA Topography



(e) ICA



(f) EEG after Artifact removal



(g) Epochs

Fig **7.** (a) Raw EEG of one of the participants (b) EEG after passing through a band-pass filter (0.2Hz to 45Hz) (c) Comparing Power spectral density before and after filtering (d) Brain Topography (e) Shows different ICAs (f) EEG after ICA decomposition (g) Shows Epochs of length (-0.2s to 1s).

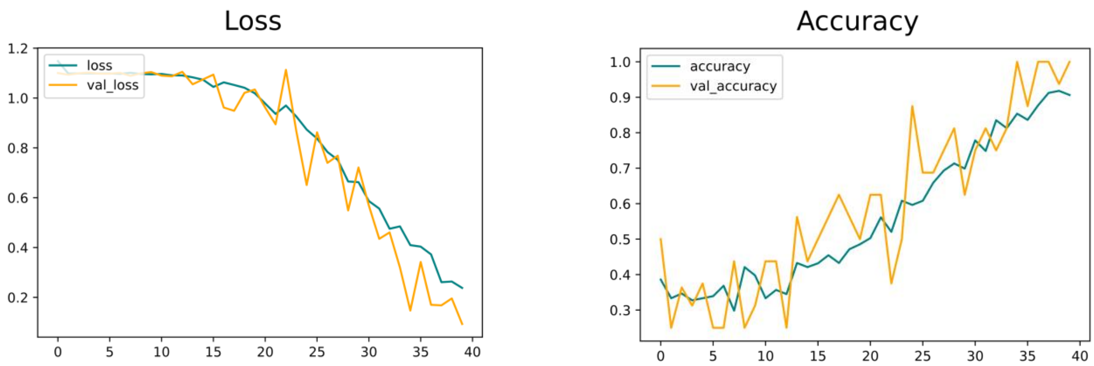
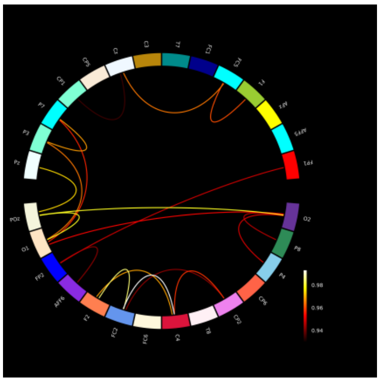
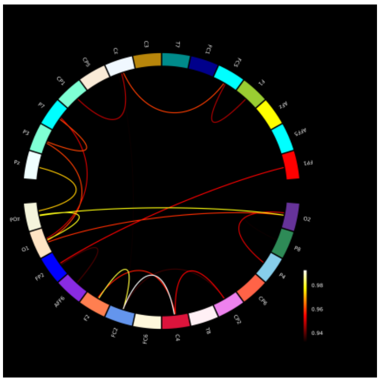


Fig 8 a) shows a loss on the training and validation dataset over 40 epochs b) shows the modelaccuracy on the train and validation dataset over 40 epochs

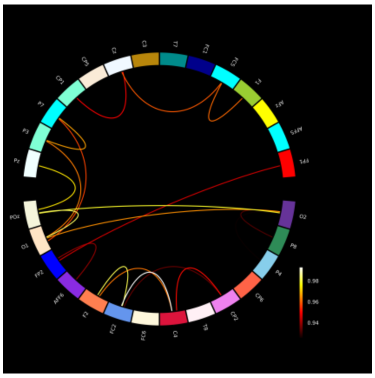
Figure 8 illustrates the progression of loss and accuracy in one of our models. The training loss consistently decreases as the number of epochs increases, indicating improved model performance. At the onsetof the first epoch, the training accuracy is at its highest point, gradually declining towards the culminationof the final epoch. Conversely, the validation accuracy exhibits variations across the epochs, reaching its lowest point towards the conclusion of the final epoch. In Figure 8(b), Throughout our analysis, it becomes evident the training accuracy of our deep learning model progressively improves with each epoch. It starts at 28 percent at the beginning of the first epoch and reaches its highest value after the last epoch. Likewise, the validation accuracy demonstrates fluctuations throughout the epochs, reaching its highest point after the final epoch, specifically at epoch 14.



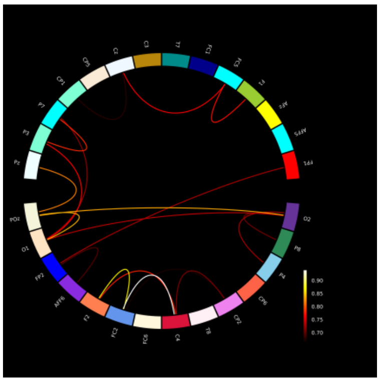
(a) PLV Low



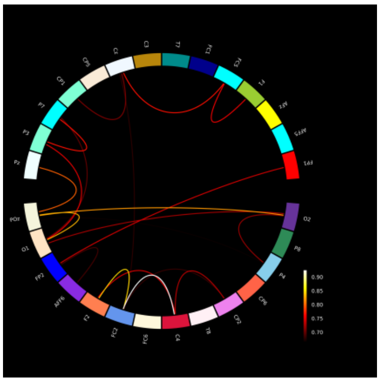
(b) PLV Medium



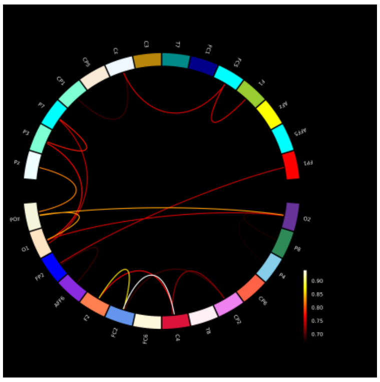
(c) PLV High



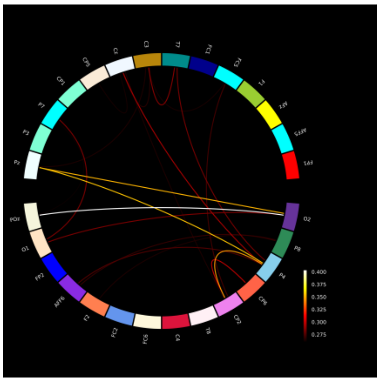
(d) COH Low



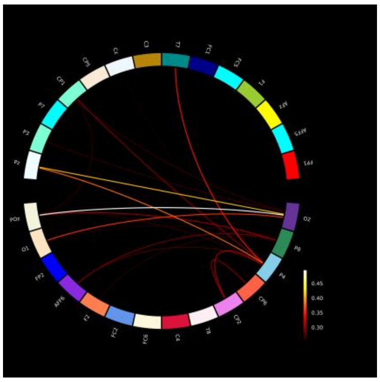
(e) COH Medium



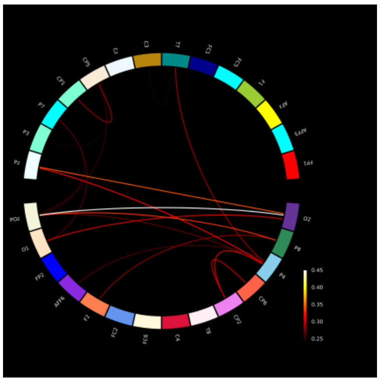
(f) COH High



(g) PLI Low

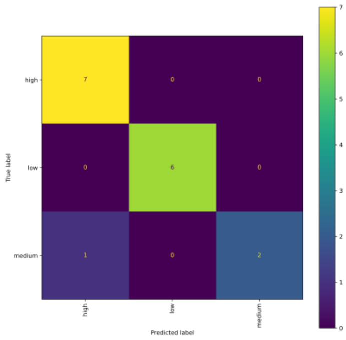


(h) PLI Medium

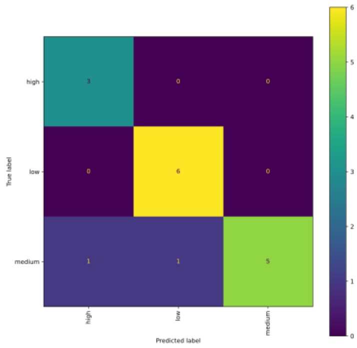


(i) PLI High

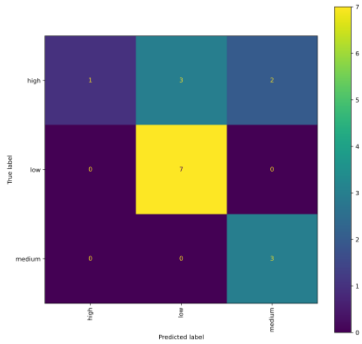
Fig 9. Brain connectivity plots for a single subject obtained using PLV, COH, and PLI methods under different cognitive workload states (low, medium, and high).



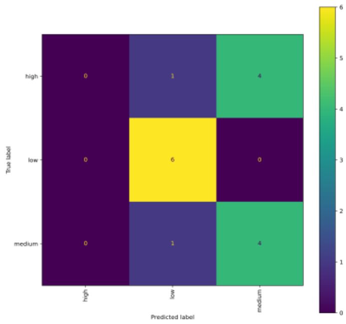
PLV-CNN(A)



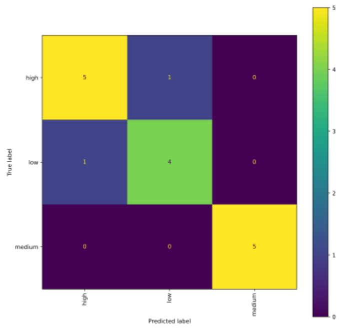
PLV-CNN(B)



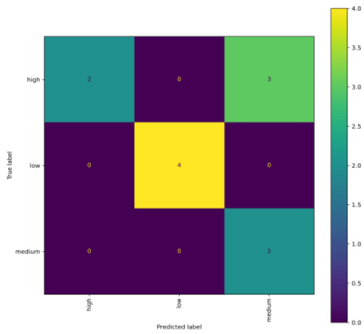
PLI-CNN(A)



PLI-CNN(B)

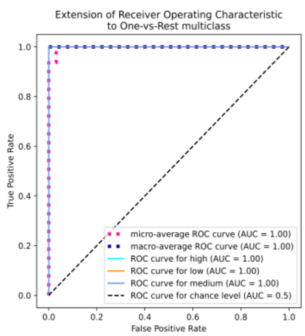


COH-CNN(A)

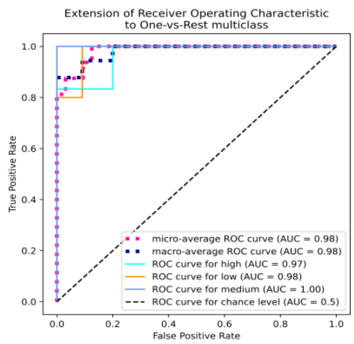


COH-CNN(B)

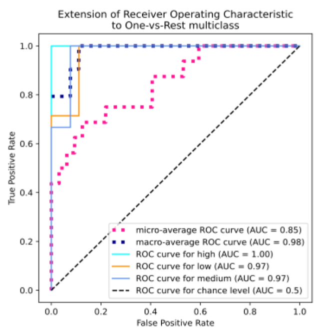
Fig10. Confusion Matrix of different combinations of CNN Models and function connectivity feature



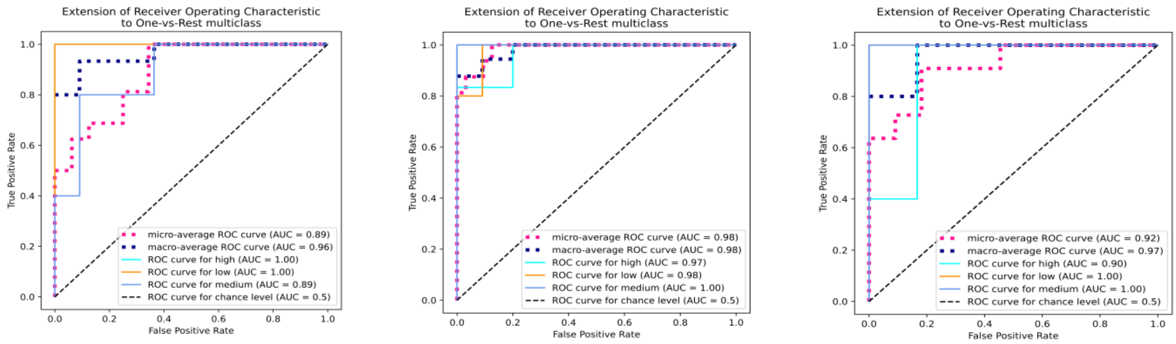
PLV-CNN(A)



PLV-CNN(B)



PLI-CNN(A)



PLI-CNN(B) COH-CNN(A) COH-CNN(B)

Fig11. ROC curves of different combinations of CNN Models and function connectivity feature

Table 1: Functional Connectivity-Based Feature Performance Comparison

Comparison Analysis	PLV	PLI	COH
CNN-A	93.75%	68.75%	87.5%
CNN-B	87.5%	62.5%	72.72%

5. Conclusion

This study aimed to develop a cognitive workload classifier capable of assessing the state of an individual in real time, particularly in high-stress environments. To achieve this, EEG isselectedas the neuroimaging technique due to its affordability, portability, and real-time data acquisition capability. Deep learning was employed as it offers higher accuracy when dealing with large datasets. Specifically, convolutional neural networks (CNN) were utilized to extract features from brain connectivity maps and train models. CNNs have demonstrated superior performance in image classification compared to traditional machine learning models, thanks to their layered neural network structure consisting of hidden neurons/units. Two different CNN architectures were implemented in this study, sharing the same convolution layers configuration but differing in the configuration of dense layers. The deep learning models achieved a remarkable accuracyof 93.75 % using PLV in CNN-A architecture, 87.5% accuracy by using Coherency in CNN-A Architecture, and 68.75% using PLI in CNN-A architecture. The architecture developed in this research holds promise for accurate monitoring of cognitive states and has potential applications in brain-computer interfaces (BCI). The brain connectivity algorithms employed enabled the rapid and precise generation of brain connectivity maps and matrices from raw EEG data. Looking ahead, incorporating brain connectivity measures with other machine learning and deep learning algorithms can further enhance the performance of existing models, particularly in tasks involving higher-order cognitive processes such as complex decision-making. The strong correlation observed between cognitive classification and subject-specific categorization also suggests the potential for personalized assistance, such as in educational settings and other domains.

Data availability

Data sharing is not applicable to this article.

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Conflict of interest

The authors declare that they have no conflict of interest.

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