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Deep Learning-Based Classification of Cognitive Workload Using Functional Connectivity Features

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Abstract. Cognitive workload plays a vital role in tasks that demand dynamic decision-making, especially under high-risk and time-sensitive conditions. An excessive workload can lead to unexpected and disproportionate risks, whereas insufficient workload may cause disengagement, undermining task performance. This underscores the importance of maintaining an optimal level of mental focus in high-pressure situations to ensure successful task execution. This study leverages deep learning methods alongside functional connectivity measures to classify cognitive workload levels. Using the N-back EEG dataset, functional connectivity metrics such as Phase Locking Value (PLV), Phase Lagging Index (PLI), and Coherency are extracted after data pre-processing. These metrics, characterized as directed or non-directed, enable efficient computational analysis. A convolutional neural network (CNN) classifier is employed to categorize cognitive workload into three levels: low (0-back), medium (2-back), and high (3-back). The CNN-A architecture achieves peak performance with an accuracy of 93.75% using PLV, 87.5% using Coherency, and 68.75% using PLI. This research provides a foundation for extending the classification of cognitive workload to more intricate, real-time, and practical scenarios, paving the way for wider applications in high-stakes environments.

Keywords: Cognitive workload, Deep Learning, CNN, EEG, Functional Connectivity, Connectivity Metrics

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1. Introduction

Cognitive workload describes the mental effort necessary for successfully completing tasks. While long-term memory stores information for extended durations, working memory is responsible for temporarily managing and processing information. Efficient utilization of working memory is vital for activities such as solving mathematical problems, reading, and acquiring new knowledge. The effort exerted by working memory to accomplish a task accurately is referred to as cognitive workload.

In modern life, we are constantly surrounded by a flood of sensory inputs. Sensory memory briefly processes and retains the most critical information, passing it to working memory for evaluation. At this stage, working memory decides which information should be further processed or discarded. On average, working memory can handle between five to nine pieces of information simultaneously.

The way the brain organizes and transfers information into long-term memory is central to Cognitive Load Theory. Information is structured into knowledge frameworks, or "schemas," based on its intended application. For instance, distinct schemas are formed for concepts like animals, dogs, cats, and mammals, enabling efficient information processing and recall.

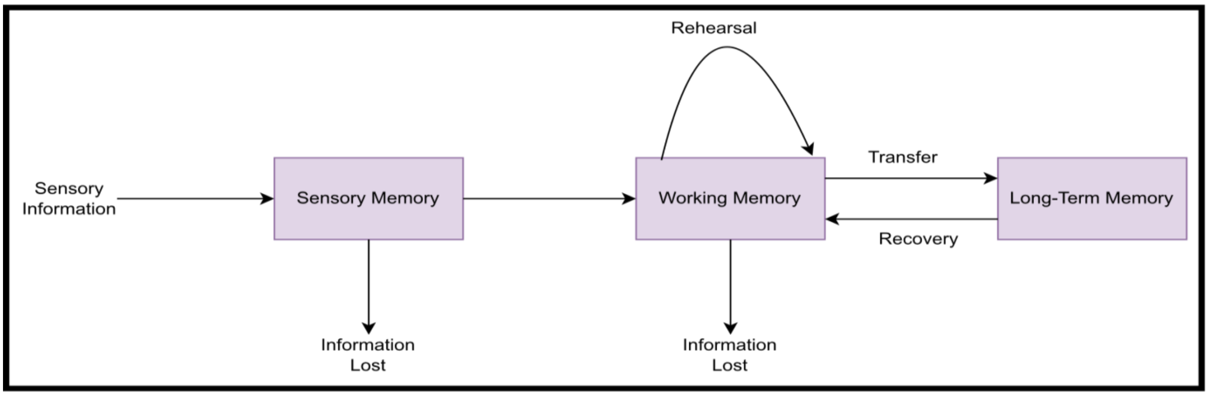


Figure 1. Information Processing Model

In tasks involving human-machine collaboration, assessing an individual's cognitive workload is crucial. The cognitive load experienced during a task is directly influenced by the speed and efficiency of information processing. Excessive workload can lead to unexpected and significant risks, while insufficient workload may result in disengagement from the task. This underscores the importance of maintaining an optimal cognitive load in high-risk scenarios to ensure effective task execution. Emotional intelligence and stability also play a significant role in determining cognitive workload. Research has established a connection between emotional quotient and specific cognitive skills. Consequently, categorizing cognitive workload could serve as a valuable indicator of emotional intelligence and task reliability.

This study focuses on categorizing cognitive workload into three levels: low, medium, and high. Functional connectivity features extracted from EEG signals are used alongside deep learning models to achieve this classification. The features considered include Phase Locking Value (PLV), the Imaginary Part of Coherency, and Phase Lagging Index (PLI), which are used to construct connectivity graphs that serve as inputs to Convolutional Neural Network (CNN) models.

The dataset utilized in this study is the publicly available N-back dataset, as referenced in [19-20]. This dataset is particularly suitable because cognitive load increases with the value of 'n', requiring participants to recall the nth previous element to complete a given task. After training the CNN models, a performance evaluation is conducted to identify the most effective combination for cognitive workload classification.

2. Literature Survey

Cognitive workload refers to the mental capacity required to perform various tasks, including mathematics, sports, and coding. It represents the amount of working memory engaged at a given moment. When working memory becomes overloaded, an individual’s ability to think and make decisions is significantly impaired.

Although measuring cognitive workload is crucial, it remains a challenging task. Initially, researchers used subjective measures such as interviews, questionnaires, and quizzes, where participants self-reported their mental state to evaluate cognitive load. However, these methods have limitations as they are based on personal assessments, which can be unreliable, biased, and inconsistent. Additionally, these approaches rely on post-task surveys, making real-time cognitive load analysis impossible. Studies such as [1] have explored this with tools like the Subjective Workload Assessment Test (SWAT).

Due to the subjective nature and lack of real-time data from questionnaire-based methods, cognitive workload research, particularly in brain-related activities, faces significant barriers [2]. To make cognitive analysis more accurate and generalizable, two approaches are considered: 1) invasive methods that require surgical procedures, and 2) non-invasive methods, which do not require skin penetration and are preferable in brain analysis. Non-invasive techniques like neurophysiological signals enable real-time cognitive load analysis. Brain-Computer Interfaces (BCIs), which have evolved significantly since the 1960s, are one such technology that uses brain imaging methods for assistive and rehabilitative applications [3].

Brain imaging techniques, such as electroencephalogram (EEG), functional magnetic resonance imaging (fMRI) [4], and near-infrared spectroscopy (NIRS), provide valuable insights into cognitive states. Among these, EEG stands out for its cost-effectiveness, high temporal resolution, and ease of implementation. EEG captures electrical signals from the brain through electrodes placed on the scalp, providing real-time insights into cognitive workload. Unlike fMRI, EEG has a high sampling rate and offers more convenient data collection, making it ideal for time-series analysis of cognitive functions. However, the electrical signals recorded by EEG are weak and must be amplified for effective analysis.

EEG has become a widely accepted tool for real-time cognitive workload assessment [5-7]. Various EEG characteristics, including frequency, temporal, spatial, and time-frequency features, are analyzed to assess different brain activities. Common methods for time-domain analysis of EEG include statistical characteristics, Event-Related Responses [8], Hjorth parameters, and higher-order crossing analysis [9]. Frequency-domain analysis has also been used to evaluate states like sleepiness, calmness, engagement, and activity, with EEG frequencies divided into sub-bands [10]. Machine learning techniques are then applied to these features for further analysis. Motamedi-Fakhr et al. [11] provided an overview of over 15 commonly used EEG characteristics for studying human sleep, including coherence analysis and wavelet transforms, while Rashid et al. [12] discussed challenges in current approaches and potential solutions.

Although earlier studies on cognitive load estimation utilized EEG data, they often limited their analysis to binary classifications (low vs. high cognitive load) and focused on computationally intensive features, which are unsuitable for real-time applications. Zhang et al. [13] employed CNN and RNN models for binary classification of cognitive workload using EEG topographic maps, achieving an accuracy of 88.9%. Another study extended this approach to classify cognitive workload into three levels using EEG topographic maps and CNN, improving accuracy to 91.9% [14].

EEG data offers insights into brain activity by capturing signals from specific regions, revealing connectivity between different brain areas, and highlighting activity levels across the brain during different tasks. This facilitates the exploration of key characteristics tied to specific cognitive states. Understanding brain connectivity is critical, as functional connectivity significantly impacts cognitive load and is essential for understanding cognitive processes.

Dimitrakopoulos et al. [15] used the n-back and mental arithmetic datasets for binary cognitive load classification using SVM, achieving 88% accuracy for n-back tasks and 87% for cross-task analysis. However, some functional connectivity features, like Phase Locking Value (PLV), can be affected by volume conduction, which distorts EEG data. Volume conduction occurs when electrical signals from distant sources interfere with local measurements, leading to inaccurate data. Cornelis J. Stam et al. [16] addressed this issue by quantifying phase synchronization and comparing phase coherence with imaginary coherency to reduce volume conduction errors.

Anmol Gupta et al. [17] used EEG-based connectivity features and deep learning models for subject-specific multi-class classification of cognitive workload levels (high, low, and medium), achieving 97.92% accuracy. PLV, Mutual Information (MI), and Phase Transfer Entropy (PTE) were the connectivity features used, with CNN-LSTM, LSTM, and CNN models yielding the best performance using PLV and MI combinations, achieving up to 95.83% accuracy.

Cognitive load, which represents the mental effort required for various tasks, is increasingly assessed using non-invasive brain imaging methods such as electroencephalography (EEG) and near-infrared spectroscopy (fNIRS). EEG, with its high temporal resolution, is particularly effective for real-time cognitive load monitoring, as demonstrated by Cohen [18], who explored phase-based connectivity and its impact on cognitive state classification. Recent studies, like Shin et al. [19], have integrated EEG with fNIRS to provide a comprehensive view of brain activity during cognitive tasks. Additionally, machine learning (ML) techniques, including deep learning models, have been employed to classify cognitive load from EEG signals, with Barua et al. [20] successfully using ML for driver cognitive load classification. The fusion of EEG with other physiological signals, such as ECG, has further enhanced classification accuracy, as shown by Xiong et al. [21]. While these advancements hold promise, challenges such as signal noise and real-time application remain, calling for ongoing improvements in signal processing and model optimization.

Zarjam et al. [22] applied wavelet entropy-based EEG features and ANN models for multi-class cognitive workload classification into seven levels, achieving 98.44% accuracy. Mingkan Shen et al. [23] utilized functional connectivity features from EEG and 3D-CNN deep learning models to identify schizophrenia with 97.74% accuracy, highlighting the role of brain connectivity in mental health assessments. Functional connectivity, such as mutual information algorithms, is used to assess brain region connectivity, offering new insights into cognitive workload. Shau Yang et al. [24] proposed a novel method to assess mental workload using EEG signals with deep learning. This method leveraged a stacked denoising autoencoder (SDAE) and a feature mapping layer to extract personalized characteristics from EEG data. The SDAE approach, termed Ensemble SDAE Classifier with Local Information Preservation (EL-SDAE), achieved an impressive accuracy of 92% in subject-average classification, outperforming other classifiers.

3. **Methods**

The architecture outlined in Fig. 2 represents the EEG processing pipeline. The process begins with the acquisition of raw EEG data, which is loaded into memory for further analysis. EEG data can be stored in various formats depending on the equipment used. For instance, BrainVision uses a triplet of EEG, VHDR, and VMRK files, while BioSemi amplifiers store the data in BDF files, a variant of the European Data Format. Additionally, Neuroscan amplifiers utilize proprietary CNT files for storing EEG data.

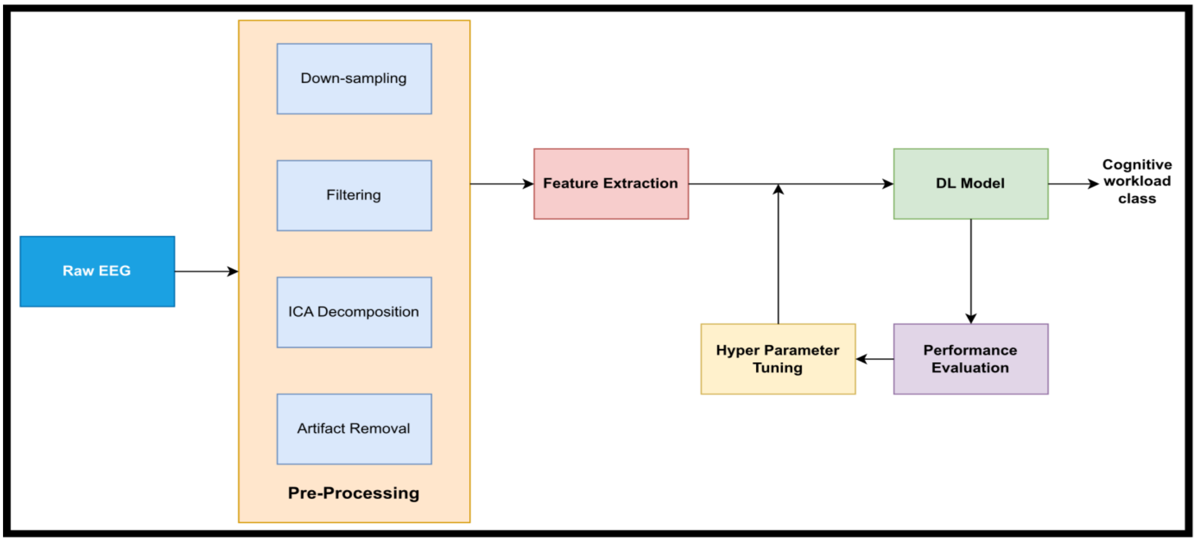


Figure 2. Architecture

The architecture can be generally categorized into three main components:

1. Pre-processing
2. Feature Extraction
3. Implementation of Deep Learning Model

3.1 Pre-processing

Pre-processing plays a vital role in transforming raw data into a format more suitable for analysis, improving its interpretability, and gaining a clearer understanding of the underlying neural signals. In this study, the MNE package in Python was used for the pre-processing tasks.

During this process, it's important to address potential loss of spatial information in the signals recorded from the brain, as this can result in inaccuracies when representing the true neural activity. Additionally, EEG data is often contaminated by noise, which can obscure weaker signals that are still significant. Other common sources of distortion include eye blinks and muscle movements.

To overcome these challenges, one effective strategy is the application of frequency integration and filtering techniques to the digital signal [25]. These methods help eliminate unwanted frequencies or retain specific ones, thereby enhancing the quality of the data for subsequent analysis.

3.2 Down-sampling

The EEG data consists of three channels, each with a sampling rate of 1000 samples per second (1000 Hz). Given that each sample is represented as a 32-bit float, the total data throughput per second is 960,000 bits (calculated as 30 * 1000 * 32).

To reduce the data size while maintaining essential information, down-sampling was applied, lowering the sampling rate to 256 Hz [17]. After down-sampling, the total throughput becomes 245,760 bits per second (calculated as 30 * 256 * 32).

3.3 Filtering

Medical research classifies EEG waves into several frequency sub-bands: beta (13–30 Hz), alpha (8–13 Hz), theta (4–8 Hz), delta (1–4 Hz), and gamma (30–80 Hz). However, these signals are often obscured by noise.

A common pre-processing step in EEG data analysis is the application of digital filters, which enhance the Signal-to-Noise Ratio (SNR) by minimizing the influence of undesired frequencies. These filters are effective in suppressing high-frequency noise such as electromyographic activity, 50/60 Hz line noise, and low-frequency skin potentials. By using digital filtering, the quality and clarity of the EEG signal are improved, making it easier to extract meaningful information while reducing disturbances. For cognitive workload analysis, the required frequency range is 4–30 Hz. Therefore, a Band-Pass filter is applied between 0.2 Hz and 45 Hz to remove unnecessary data and noise [22].

3.4 Artifact (Ocular Artifact) Removal

Artifact removal is a critical step in EEG signal processing, essential for ensuring data accuracy by eliminating unwanted signals that can contaminate or distort the results. One common type of artifact is ocular artifact, which arises from eye movements, both horizontal and vertical, as well as blinking. These ocular artifacts can severely affect the accuracy and interpretation of EEG data by introducing noise that masks or distorts underlying brain activity. Therefore, effectively removing ocular artifacts is crucial for obtaining reliable EEG data.

Several techniques can be employed to remove ocular artifacts from EEG signals. Independent Component Analysis (ICA) is a widely used method that decomposes mixed signals into independent components, allowing for the identification and removal of those associated with ocular activity. Regression-based approaches, where regression models are trained to predict ocular artifacts from auxiliary channels like electrooculogram (EOG) data, can also be used. The predicted ocular artifacts are then subtracted from the original EEG signals to eliminate the contamination.

In addition to these methods, advanced signal processing techniques, such as adaptive filtering and wavelet-based approaches, can be applied to efficiently detect and remove ocular distortions. Properly eliminating ocular artifacts ensures cleaner, more consistent EEG data, facilitating the accurate analysis and interpretation of the brain's underlying activity.

3.5 ICA Decomposition

Independent Component Analysis (ICA) was employed to eliminate ocular artifacts from the EEG data. EEG signals are composed of electrical potentials originating from various sources, including brain activity and external influences such as eye movements and blinking. Each of these sources, including ocular artifacts, projects its unique topography onto the scalp maps, which ICA can separate, allowing for the removal of the ocular components while preserving the underlying brain signals.

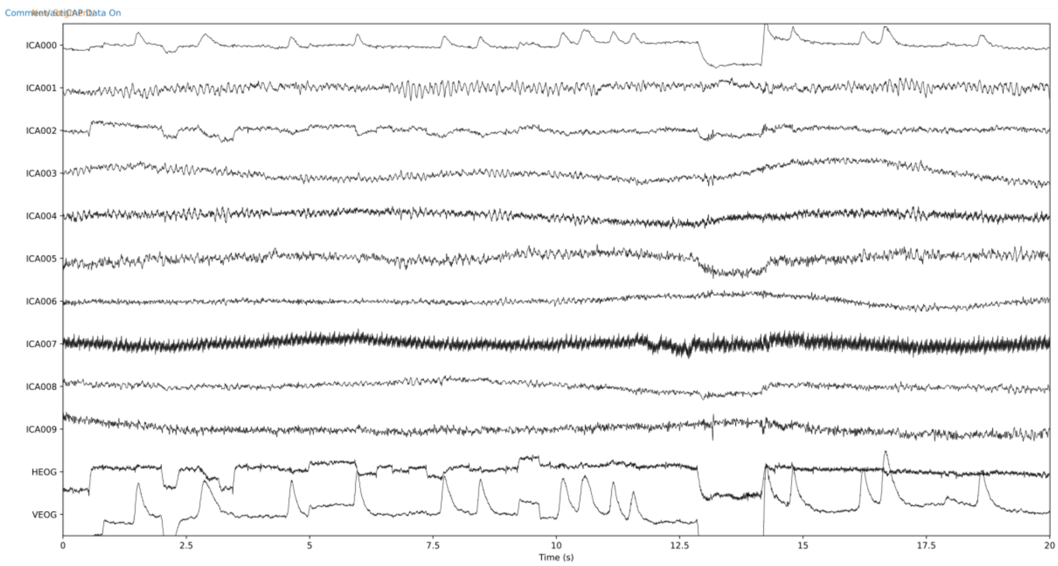


Figure 3. Independent Component Analysis

Figure 3 illustrates the various components of our EEG signals, with ICA000 and ICA002 identified as ocular artifacts. Independent Component Analysis (ICA) is particularly effective when there is no prior knowledge of the sources or the mixing process, and the observed signals are a linear combination of unknown source signals.

In EEG analysis, ICA can be utilized to distinguish the contributions of different brain sources to the recorded data. It aids in isolating specific brain activities or artifacts, thereby improving the clarity and interpretation of EEG signals. By applying ICA, we were able to examine individual scalp maps and channels separately, enabling the exclusion of specific channels based on their activity levels and regions. This method provided an efficient means of enhancing the data quality through additional cleaning steps.

3.6 Epoch and Event Extraction

EEG epoching refers to the process of isolating specific time segments from a continuous EEG signal, typically synchronized with an event such as a visual stimulus. These segments, known as "epochs," simplify calculations and facilitate analysis within defined time constraints. In our study, event files were imported and used to retrieve various events based on their event IDs, enabling us to examine the frequency and duration of events within short time intervals.

Specifically, epoch separation was performed to extract 0-back, 2-back, and 3-back events for feature extraction, followed by the application of a deep learning model for classification. Figure 4 illustrates the occurrence of these events within our dataset.

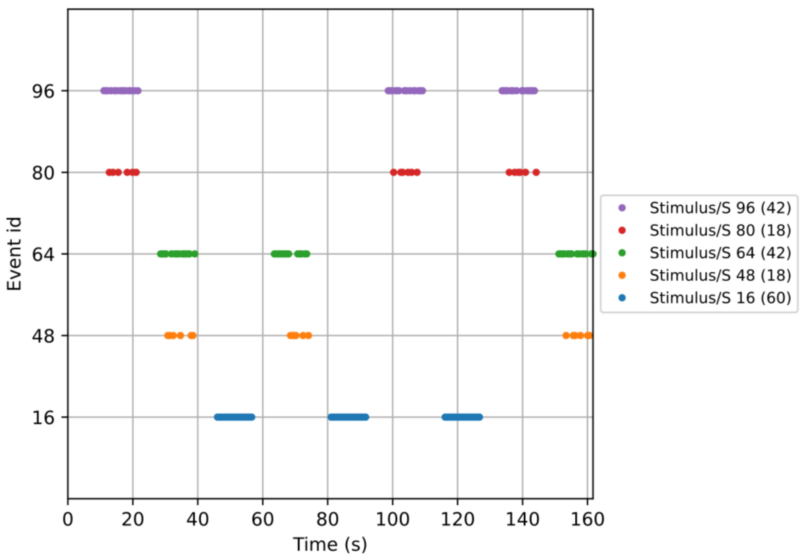


Figure 4. Events and their occurrence in one of the subject EEG data

3.7 Feature Extraction

Brodmann's research has mapped specific regions of the brain to distinct functions, forming a functional brain map. During cognitive tasks, various specialized brain areas are activated, and the brain coordinates the flow of information dynamically to perform the task. To study this dynamic coordination, two primary methods are used: oscillation and spike rate analysis. This study focuses on exploring dynamic coordination through oscillation rather than spike rate analysis, due to anatomical constraints and feasibility issues. Functional connectivity is employed as a technique to quantify neuronal associations and analyze the coordination between brain regions. The research utilizes both directed and non-directed model-based approaches to examine functional connectivity, employing metrics such as PLI, imaginary coherency, and PLV. These measures help assess the integration and relationships between neural signals, offering valuable insights into the coordination and interactions among brain regions.

3.8 Phase Locking Value (PLV)

PLV (Phase Locking Value) is a technique commonly used to assess the synchronization or phase coherence in EEG signals, providing insights into the stability of phase relationships over time. It quantifies the degree of phase consistency between EEG signals, offering valuable information on their interconnection.

To calculate PLV, phase information is extracted from two signals using methods such as the Hilbert transform. Signals originating from different brain regions or sources can be represented using the Hilbert transform, allowing for the analysis of their phase relationships.

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

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

The equation below represents the phase difference between the signals at each time point.

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

The PLV is then calculated by averaging these phase differences over a defined time window.

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

A higher phase locking value (PLV) indicates increased phase synchronization between the signals, suggesting that the brain regions associated with those signals are working in a coordinated manner, with a value of 1 denoting total phase synchronization. In contrast, a lower PLV reflects weaker or less consistent phase coupling, where a value of 0 signifies no phase synchrony.

3.9 Phase lagging index (PLI)

Stam and colleagues [16] introduced the Phase Lag Index (PLI) to address the issue of volume conduction in PLV measurements. Volume conduction refers to the phenomenon where electrical signals generated by brain activity spread through the surrounding conductive mediums, such as cerebrospinal fluid and the skull, which can influence the measurements recorded by scalp electrodes.

While EEG electrodes measure the electric fields generated by the brain's electrical activity, these signals are affected by the conductivity and geometry of the surrounding tissues, leading to volume conduction. This effect can cause correlations between signals at different electrodes, even when the electrodes are not directly connected, as the electrical fields from brain activity can propagate across multiple electrodes.

To minimize the impact of volume conduction, PLI focuses on excluding phase locking centered around 0, π, 2π, and similar phase differences, thus providing a more accurate representation of functional connectivity.

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

In the equation above, the signum function (sgn) discards phase differences of 0, π, 2π, 3π, and so on, thus eliminating the influence of volume conduction. The Phase Lag Index (PLI) ranges from 0 to 1, where 0 indicates no coupling between the signals and 1 indicates that there is no volume conduction, i.e., the signals reflect true brain activity. When the PLI value is 0, it suggests that volume conduction may or may not be present.

PLI is calculated by determining the proportion of time points where the phase difference between two signals exceeds a specified threshold, typically set at 0 or π radians. If the phase difference 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, results in a higher PLI value.

PLI is a valuable measure for assessing the strength and presence of phase synchronization between EEG signals and is widely used in studies of functional connectivity and brain network interactions, helping to understand the coordination and communication between different brain regions.

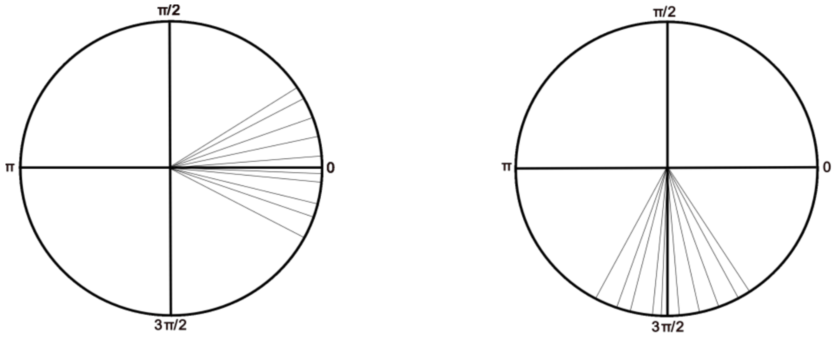


Figure 5. Illustration of Phase Lag Index (PLI) values

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.

3.10 Imaginary Coherency

The imaginary coherency is a metric employed in EEG signal analysis to evaluate the phase relationship between two signals at a specific frequency. To compute the real and imaginary components of coherency between two time series, the cross-spectrum is divided by the squared product of the power spectra of the individual signals.

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

Coherency is an all-encompassing metric that integrates both phase and amplitude information in the frequency domain, offering valuable insights into the relationship between two signals. It quantifies the correlation between the signals at a specific frequency. The imaginary coherency focuses on the phase relationship, while the real part reflects the amplitude correlation.

In this context, the amplitudes are denoted as A1 and A2, with Δϕ representing the instantaneous phase difference between the two time series.

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

The imaginary coherency measures the phase difference between signals at a given frequency. This approach focuses solely on the imaginary component of coherency, isolating phase information while excluding amplitude data. According to Nolte et al. [16], a non-zero imaginary part in the coherency measure suggests that the underlying sources of the two time series are not merely the result of linearly mixed, uncorrelated signals, such as those arising from volume conduction. Instead, it implies that an interaction exists between the sources.

However, it is crucial to note that the numerical value of the imaginary component alone is insufficient to assess the strength of coupling between the sources. Both the coupling strength and the amplitude of the phase difference influence the interaction.

In conclusion, while a non-zero imaginary part in the coherency measure indicates an interaction between sources; further analysis is required to determine the strength of the coupling between them.

3.11. Deep Learning Model

Deep learning, a subset of machine learning, leverages neural network principles for model development and training. It emulates the human brain's operations to identify patterns in large datasets, often offering advantages over traditional machine learning. In this study, Convolutional Neural Networks (CNN) are used due to the nature of the input data, which consists of brain connectivity plot images. CNNs are well-suited for tasks such as image classification and object recognition. These models utilize convolutional layers and pooling techniques to automatically extract important features from images.

CNNs have shown remarkable performance in various computer vision tasks, proving their ability to detect and learn key patterns from visual data.

For this research, CNN models are employed to determine workload, with brain connectivity circular plots as input images. Two CNN models are utilized to enhance the results, both sharing the same convolutional layer configuration but differing in their dense layers. The architecture includes three convolutional layers with 16, 32, and 16 filters, each using a kernel size of 3x3 and the ReLU activation function. The output of each convolutional layer is passed through a 2x2 max-pooling layer. The first CNN model has a dense layer with two fully connected layers: one with three neurons and the other with 256 neurons, using ReLU and SoftMax activation functions, respectively. The second CNN model features three dense layers with 64, 16, and 3 neurons, using ReLU, ReLU, and SoftMax activation functions, respectively. The final layer in both models consists of three neurons to classify the data into three categories. Sparse categorical cross-entropy is used as the loss function.

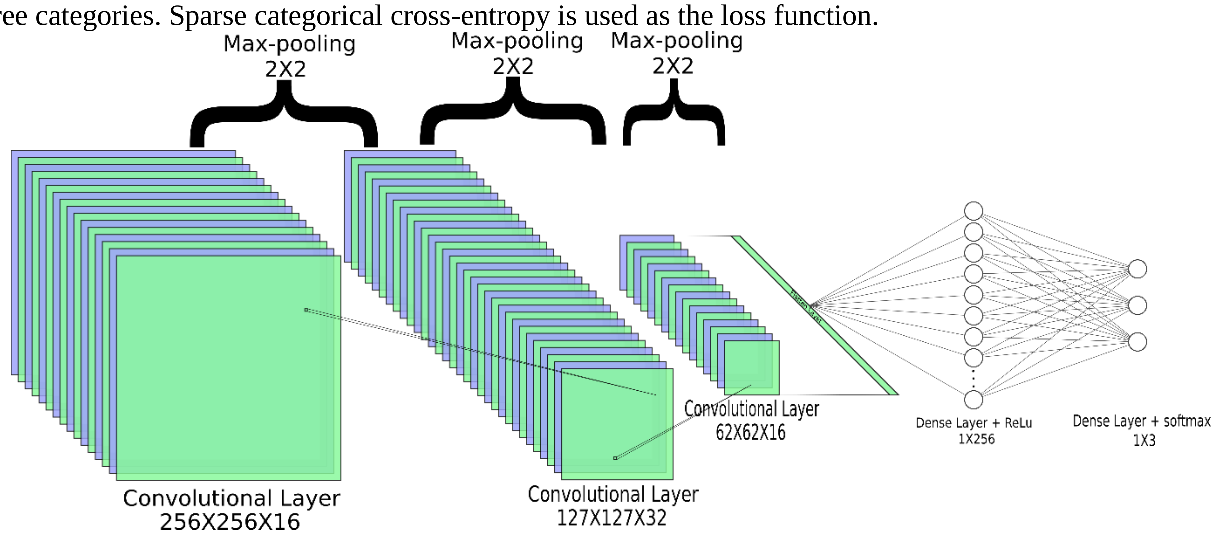


Fig 6(a) CNN-A Architecture

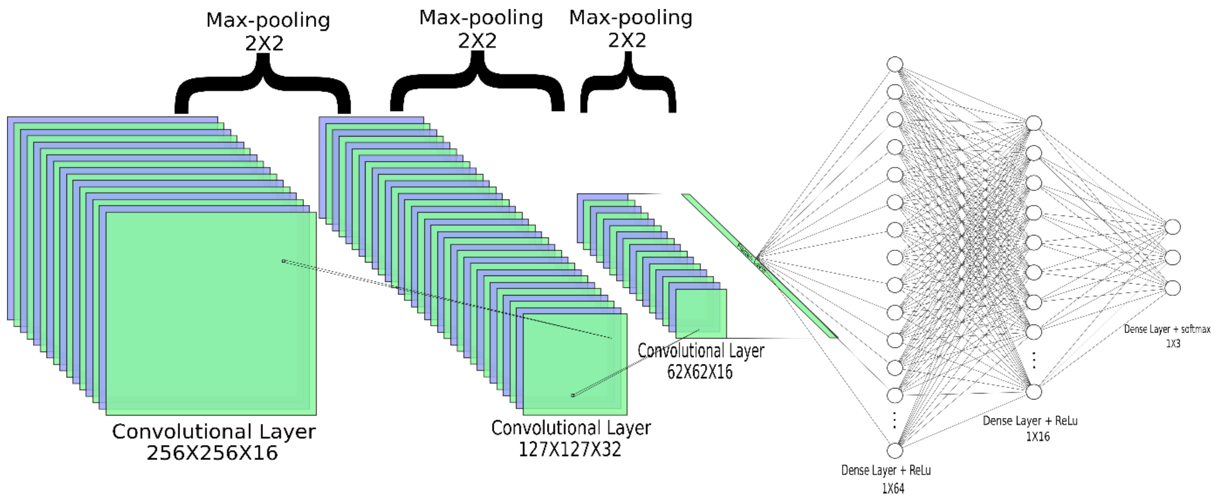
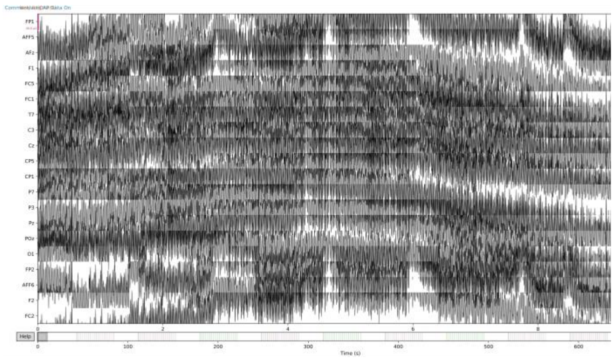


Figure 6. (b) CNN-B Architecture

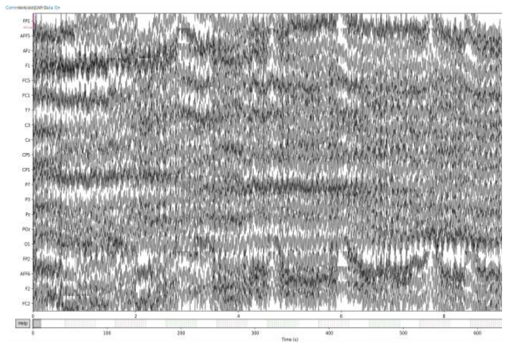
4. **Results and Discussion**

The following results are derived using the methods outlined above, starting with pre-processing, followed by feature extraction, CNN model performance evaluation, and a comparison with previous studies.

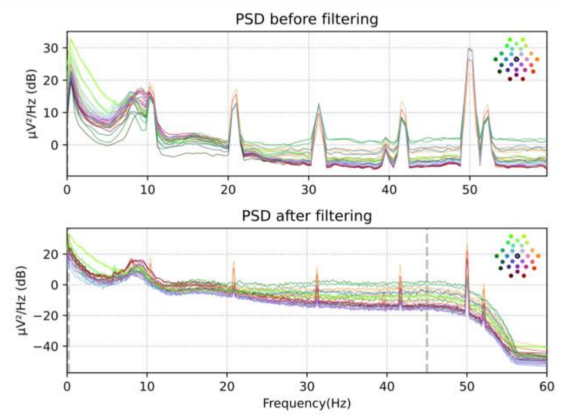
Figure 7 illustrates the complete EEG pre-processing pipeline for one participant. Subfigure (a) shows the raw EEG signal, which contains brain activity along with noise and artifacts. In (b), the signal after applying a 0.2–45 Hz band-pass filter is shown, where unwanted low- and high-frequency components are reduced. Subfigure (c) compares the power spectral density before and after filtering, highlighting the suppression of noise and preservation of relevant EEG bands. In (d), the ICA scalp topography displays the spatial distribution of independent components across the head, while (e) presents the separated independent components, some of which correspond to artifacts such as eye blinks. After removing these artifact-related components, (f) shows the cleaned EEG signal with improved signal quality. Finally, (g) depicts the segmented epochs extracted around task events (−0.2 s to 1 s), which are used for further feature extraction and classification.



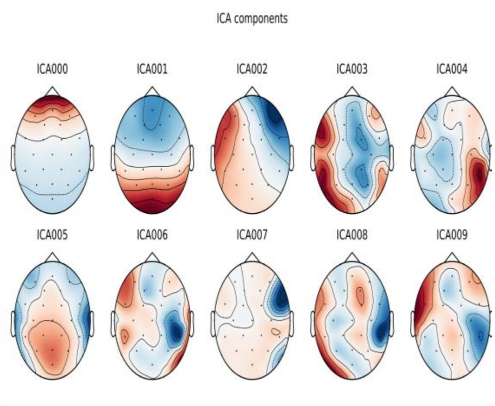
(a) Raw EEG



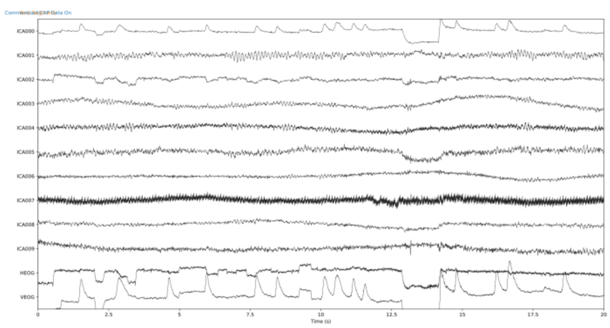
(b) EEG after Filtering



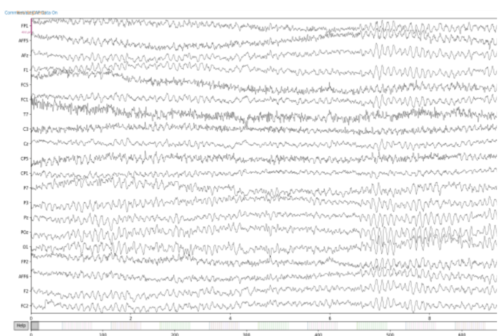
(c) PSD before and after filtering



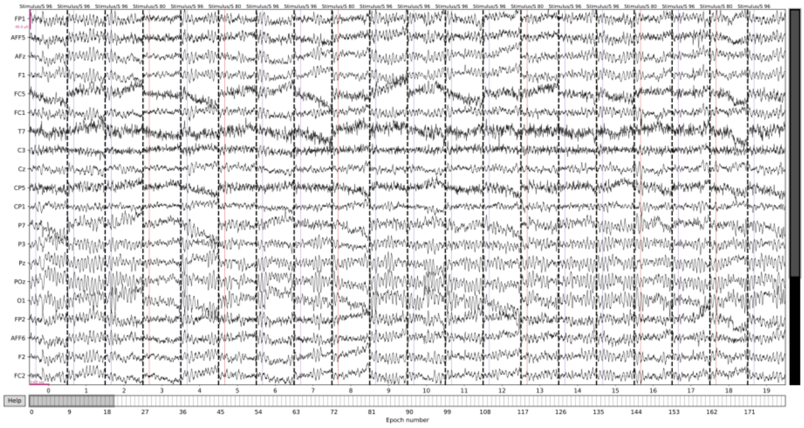
(d) ICA Topography



(e) ICAs



(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).

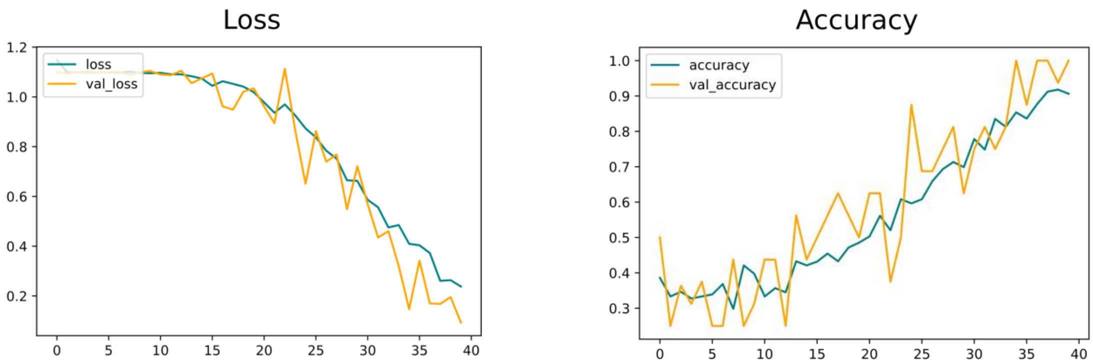


Figure 8. a) shows a loss on the training and validation dataset over 40 epochs b) shows the model accuracy on the train and validation dataset over 40 epochs

Figure 8 displays the progression of loss and accuracy for one of our models. As the number of epochs increases, the training loss steadily decreases, indicating improved model performance. At the beginning of the first epoch, the training accuracy is at its highest, gradually declining towards the end of the final epoch. In contrast, the validation accuracy shows fluctuations across epochs, reaching its lowest point at the end of the final epoch. In Figure 8(b), our analysis reveals that the training accuracy of the deep learning model steadily improves with each epoch, starting at 28% in the first epoch and achieving its peak by the final epoch. Similarly, the validation accuracy fluctuates throughout the epochs, reaching its highest value at epoch 14.

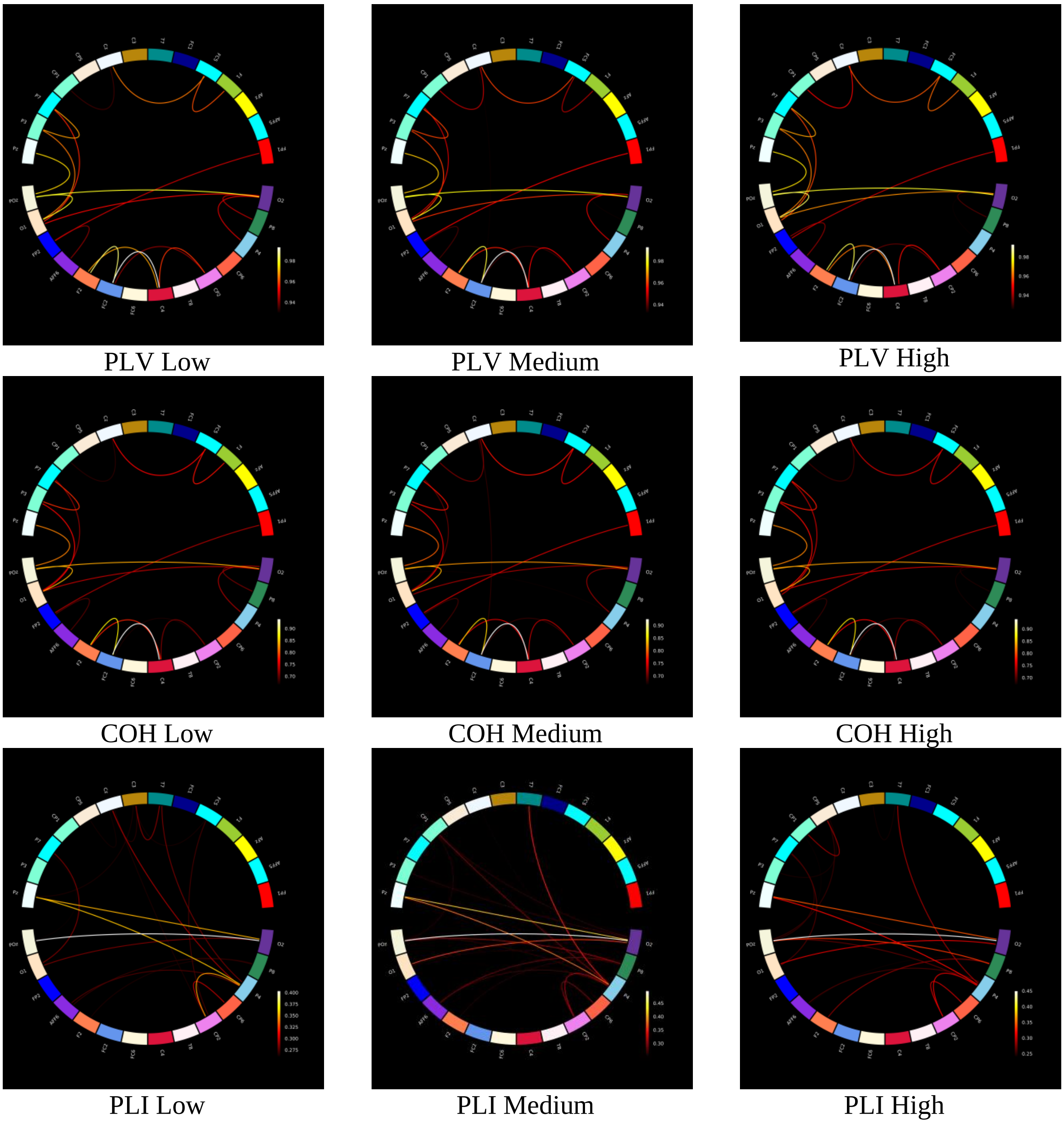


Figure 9. Brain connectivity plots for a single subject obtained using PLV, COH, and PLI methods under different cognitive workload states (low, medium, and high).

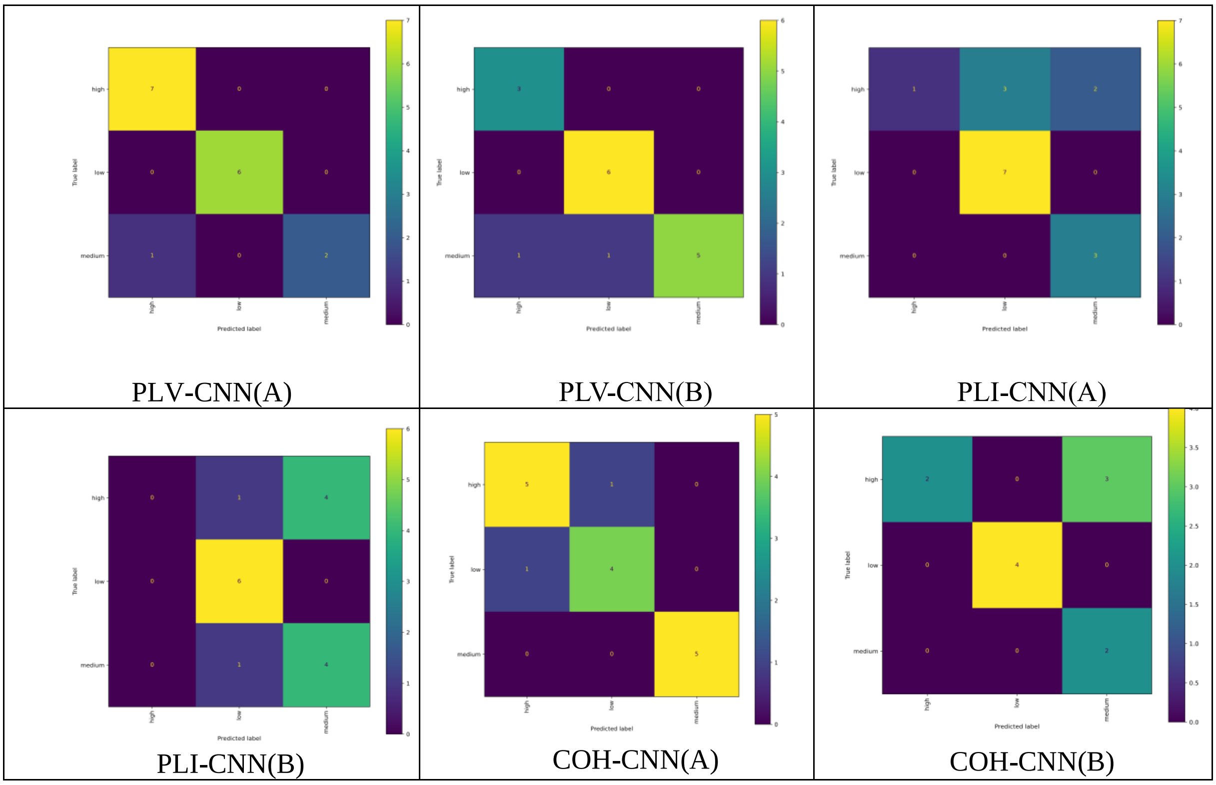


Figure 10. Confusion Matrix of different combinations of CNN Models and function connectivity feature

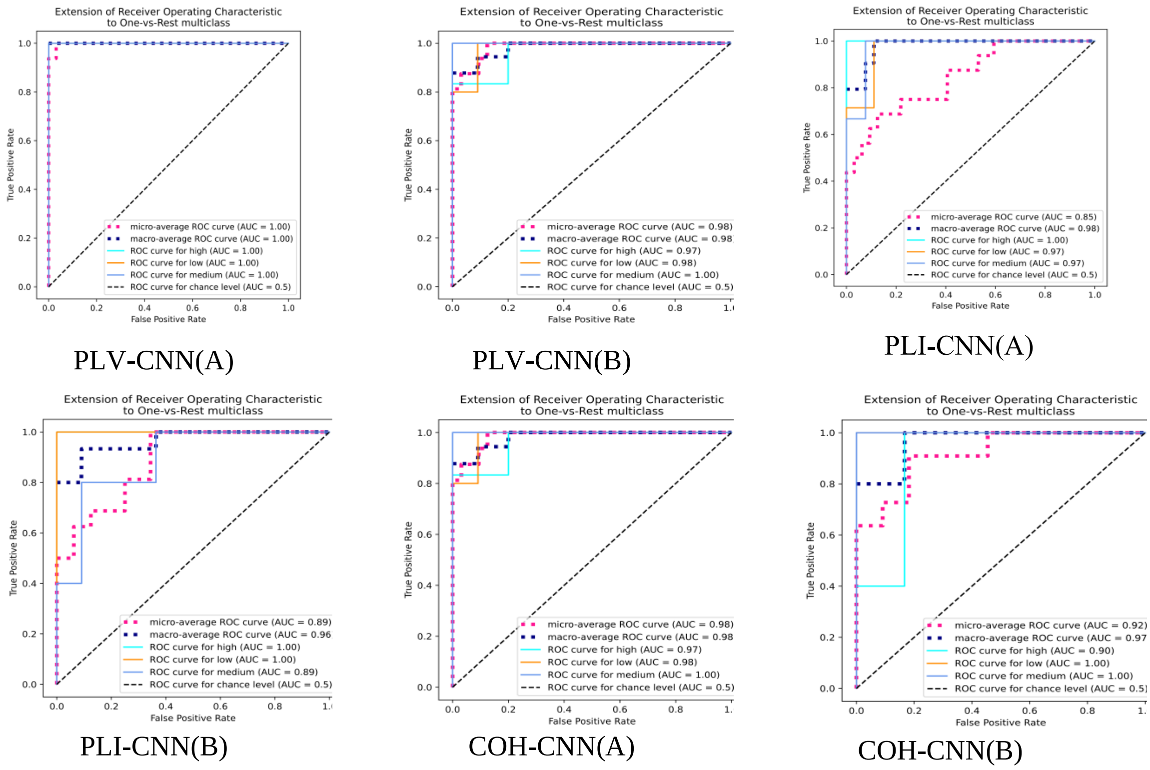


Figure 11. ROC curves of different combinations of CNN Models and function connectivity feature

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 an individual's state in real time, especially in high-stress environments. EEG was chosen as the neuroimaging technique due to its affordability, portability, and ability to acquire real-time data. Deep learning was employed for its higher accuracy in handling large datasets. Specifically, convolutional neural networks (CNNs) were used to extract features from brain connectivity maps and train models. CNNs have shown superior performance in image classification tasks compared to traditional machine learning models, thanks to their layered neural network structure with hidden neurons/units. Two distinct CNN architectures were implemented in this study, sharing the same convolutional layer configuration but differing in the dense layer setup. The deep learning models achieved notable accuracy: 93.75% using PLV in CNN-A architecture, 87.5% using Coherency in CNN-A architecture, and 68.75% using PLI in CNN-A architecture. The architecture developed holds great promise for accurately monitoring cognitive states and has potential applications in brain-computer interfaces (BCI). The brain connectivity algorithms employed enabled the efficient generation of brain connectivity maps and matrices from raw EEG data. Looking ahead, the performance of current models can be enhanced by combining brain connectivity metrics with other machine learning and deep learning techniques, especially for tasks that involve higher-order cognitive processes such as complex decision-making. The strong correlation between cognitive classification and subject-specific categorization also suggests potential for personalized assistance, particularly in educational settings and other domains.

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