

VR-EEG SYSTEM FOR GAMIFIED ASSESSMENT



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CERTIFICATE

We accept the work contained in this report as a confirmation to the required standard for the partial fulfillment of the degree of B(CE).

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VR-EEG System For Gamified Assessment

SDG No	Description of SDG	SDG No	Description of SDG
SDG 1	No Poverty	SDG 9	✓ Industry, Innovation, and Infrastructure
SDG 2	Zero Hunger	SDG 10	Reduced Inequalities
SDG 3	✓ Good Health and Well Being	SDG 11	Sustainable Cities and Communities
SDG 4	Quality Education	SDG 12	Responsible Consumption and Production
SDG 5	Gender Equality	SDG 13	Climate Change
SDG 6	Clean Water and Sanitation	SDG 14	Life Below Water
SDG 7	Affordable and Clean Energy	SDG 15	Life on Land
SDG 8	Decent Work and Economic Growth	SDG 16	Peace, Justice and Strong Institutions
		SDG 17	Partnerships for the Goals



Range of Complex Problem Solving			
	Attribute	Complex Problem	
1	Range of conflicting requirements	Involve wide-ranging or conflicting technical, engineering and other issues.	
2	Depth of analysis required	Have no obvious solution and require abstract thinking, originality in analysis to formulate suitable models.	
3	Depth of knowledge required	Requires research-based knowledge much of which is at, or informed by, the forefront of the professional discipline and which allows a fundamentals-based, first principles analytical approach.	✓
4	Familiarity of issues	Involve infrequently encountered issues	
5	Extent of applicable codes	Are outside problems encompassed by standards and codes of practice for professional engineering.	
6	Extent of stakeholder involvement and level of conflicting requirements	Involve diverse groups of stakeholders with widely varying needs.	✓
7	Consequences	Have significant consequences in a range of contexts.	
8	Interdependence	Are high level problems including many component parts or sub-problems	
Range of Complex Problem Activities			
	Attribute	Complex Activities	
1	Range of resources	Involve the use of diverse resources (and for this purpose, resources include people, money, equipment, materials, information and technologies).	✓
2	Level of interaction	Require resolution of significant problems arising from interactions between wide ranging and conflicting technical, engineering or other issues.	✓
3	Innovation	Involve creative use of engineering principles and research-based knowledge in novel ways.	✓
4	Consequences to society and the environment	Have significant consequences in a range of contexts, characterized by difficulty of prediction and mitigation.	
5	Familiarity	Can extend beyond previous experiences by applying principles-based approaches.	

UNDERTAKING

I certify that research work titled “VR-EEG system for gamified assessment” is my own work. The work has not been presented elsewhere for assessment. Where material has been used from other sources it has been properly acknowledged / referred

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DEDICATION

This thesis is dedicated to Allah SWT for His innumerable blessings, guidance and mercy throughout my academic journey. I would like to express my sincere appreciation to my dear parents for their unconditional love, constant prayers, sacrifice and constant support throughout this process. Their encouragement has always been the greatest strength and motivation of mine. This work is also dedicated to my family, teachers and friends for their constant guidance, encouragement and support.

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ABSTRACT

Assessing the cognitive workload is a fundamental need for the design of intelligent and adaptive human computer interaction (HCI) systems, especially in immersed environments where the difficulty level of a task can dynamically affect a user's mental state. In this research, a VR-EEG framework for cognitive workload assessment based on the electroencephalography (EEG) signal during a memory-based VR task is introduced, which is gamified to make the task more realistic. The EEG data were recorded from 16 participants using an OpenBCI Cyton 8-channel biosensing board when participants were asked to complete tasks under four different workload conditions: Relaxation, Easy, Medium, and Hard. Three different deep learning models were designed and tested under the same experimental setup. The first model, Multi-Branch Attentive EEGNet (MBA-EEGNet), uses multi-branch temporal feature extraction, depthwise spatial convolution and channel attention to efficiently learn discriminative EEG representations. The second model is Multi-Scale Dynamic Graph Cross-Attention Conformer (MS-DGCA Conformer), which combines multi-scale convolution, dynamic graph-based spatial learning, cross-attention, and Conformer-based feature extraction to model the spatial and temporal relationships of EEG signals. Last, the proposed MS-DGCA-MBA-EEGNet Hybrid model is an integration of complementary features of MBA-EEGNet and MS-DGCA Conformer that aims to enhance the representation of both temporal EEG dynamics and spatial connectivity patterns. The evaluation with the topics proved the mean classification accuracy of MBA-EEGNet as **79.23%** and that of MS-DGCA Conformer as **76.74%** when subject wise evaluation was performed. The MS-DGCA Conformer also showed a good mean accuracy of 78.28% across 5 folds of the cross validation, which shows that it is generalizing well. The proposed MS-DGCA-MBA-EEGNet Hybrid model performed best on all the subjects (81.50% mean, across the 16 participants) compared to the individual architectures. The findings in this work show the power of this new approach that integrates convolutional, attention-based, graph-based, and Conformer-based feature learning to provide accurate multi-level cognitive workload estimation in immersive VR applications. A cognitive workload assessment of VR users in the past required the researcher to observe from afar, carry VR equipment, or choose the appropriate participant.

Keywords: EEG, Cognitive Workload Assessment, Virtual Reality, MBA-EEGNet, MS-DGCA Conformer, Hybrid Deep Learning, Brain-Computer Interface, EEG Classification, Multi-Scale Feature Learning

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Chapter 1

Introduction

Intelligent computing systems have evolved rapidly, changing the human computer interaction paradigm. In the context of these new technologies, Virtual Reality (VR), Artificial Intelligence (AI) and Brain Computer Interfaces (BCIs) [1, 2] have been of special interest for the possibility of developing adaptive and immersive environments to be used in education, health, rehabilitation, military training and industrial automation [3, 4]. Cognitive workload is the mental load needed by the person to complete the task successfully in a given environment. It captures the interactions between task demands and the cognitive resources an individual has while performing the task. Mental overload is a condition that occurs when task demands are greater than the processing capacity of the human brain, leading to mental fatigue, slower reaction time, decreased concentration, poor decision making and decreased task performance. On the other hand, highly simple tasks might decrease vigilance and situational awareness, resulting in inattention and less operational efficiency[5, 6]. Cognitive workload is currently a subject of research with numerous applications in health-care, aviation, transportation, education, industrial automation, defence and HCI.[7, 8] In safety-critical applications like aircraft control, intelligent transportation systems, emergency response, and medical operations, real-time monitoring of the cognitive status of human operators in these applications could greatly mitigate human error and enhance safety and decision-making [8, 9]. Thus, the development of intelligent systems that continuously estimate cognitive workload during the course of task execution has been focused upon in the research.

The subject self-report questionnaires, behavioural observations and performance measures are the traditional methods used to assess cognitive workload. Although there are new and improved ways to evaluate, subjective techniques are still among the most popular such as the National Aeronautics and Space Administration Task Load Index (NASA-TLX) which are simple and easy to implement. These methods are however largely subjective and require the participants to perceive their own performance and are typically applied once the task has been completed, which is not ideal for ongoing monitoring. Behaviours such as reaction time, task completion time and the error rate are indirect measures of mental workload, but can be affected by external environmental factors and individual differences and are therefore not entirely reliable for real-world applications [3]. Since subjective and behavioral measures are limited, physiological measures have been studied as objective mea-

asures of cognitive workload, with the idea of overcoming these limitations. Physiological measures give ongoing data on the underlying processes of human cognition, and hence a more reliable measurement of mental state. One of the most successful physiological modalities to estimate cognitive workload is the so-called electroencephalography (EEG), which is a direct measurement of the electrical activity of the brain's neurons in the cerebral cortex, with excellent temporal resolution [10, 11]. EEG allows researchers to be more able to continuously monitor dynamic changes in brain activity related to attention, memory, perception, learning and decision making.

EEG is comprised of several frequency bands corresponding to various cognitive and physiological states: Delta (δ), Theta (θ), Alpha (α), and Beta (β). Several studies have shown that higher frontal Theta activity and lower Alpha power is correlated with greater cognitive load and mental effort when performing memory tasks and attention demanding tasks [12, 13]. Recent advances in Virtual Reality (VR) technology have added another layer to cognitive workload research by offering immersive and interactive experimental environments that closely replicate real-world scenarios and yet offer complete experimental control. VR provides a realistic 3D environment for participants, leading to more realistic responses of cognition and behaviour, than conventional laboratory experiments. Thus, Virtual Reality is becoming more and more popular to study human attention, learning, decision-making, and cognitive workload assessment in realistic settings [5, 7, 14]. Although considerable advances have been made in the assessment of cognitive workload using EEG, there are still a number of issues to be addressed in research. Previous studies have used publicly available EEG data acquired with traditional cognitive tasks like the N-back task, mental arithmetic or visual attention tasks. While these experimental paradigms offer a structured setting to conduct workload analysis, they do not accurately capture the complexity and dynamic interaction in immersive real-world settings [15, 16]. Moreover, most current deep learning methods are mainly focused on temporal feature extraction and ignore the intricate spatial interactions between EEG channels, which hinders the generalization of these methods between subjects and experimental settings.

In this study, researchers introduce a cognitive workload assessment framework in VR via EEG signal obtained from a memory game. To overcome these drawbacks, the authors of this research propose a cognitive workload assessment framework in VR based on EEG signals collected during an immersive VR memory game. The experimental setup was created with the Meta Quest 2 Virtual Reality headset and brain activity was recorded with the OpenBCI Cyton eight-channel EEG acquisition system (Amazon quest2, Openbci2025). The proposed VR memory game was designed

to elicit four different levels of cognitive workload: Relaxation, Easy, Medium, and Hard in order to capture the EEG signals at different levels of cognitive challenge. Prior to feeding into deep learning models for workload classification, EEG signals acquired undergo an extensive preprocessing pipeline including band-pass filtering, signal segmentation, normalization, and feature preparation. The research offers two novel deep learning architectures for multiclass cognitive workload assessment unlike traditional methods. The first proposed model, called Multi-Branch Attentive EEGNet (MBA-EEGNet), adds a multi-branch convolutional feature extraction module to the basic EEGNet framework and adds an adaptive channel attention module to enhance spatial feature representation [17]. The second proposed architecture is Multi-Scale Dynamic Graph Cross-Attention Conformer (MS-DGCA Conformer) which combines multi-scale convolution, dynamic graph learning, graph attention mechanisms, and Conformer-based temporal modelling to simultaneously capture both spatial and temporal characteristics of EEG signals [9, 18]. Classifiers accuracy, precision, recall, f1 score, confusion matrix analysis, subject-wise evaluation and 5-fold cross validation are used to assess the effectiveness of the proposed architectures. In addition, the classification capability and robustness of the two proposed models are investigated by performing a comprehensive comparative analysis between them. The findings of this research are hoped to play a part in the creation of intelligent cognitive monitoring systems which can continuously estimate users' mental workload in real-time. These systems can be applied in many fields such as adaptive learning, healthcare, neuroergonomics, intelligent transportation, industrial automation and other human-centred artificial intelligence systems, where maintaining optimal cognitive performance is essential. ent healthcare applications [3, 9, 16] to name a few. Cognitive Workload Assessment using EEG

One of the most commonly used non-invasive neurophysiological tools for monitoring brain activity is electroencephalography (EEG), which has become a critical tool for cognitive workload assessment. EEG has high temporal resolution, and enables the analysis of rapid changes in brain function during cognitive processing, via electrodes positioned on the scalp [10, 11]. EEG has been widely used in neuroscience, brain-computer interfaces (BCIs), neuroergonomics and intelligent human-computer interaction systems due to its real-time monitoring capabilities of neural activities.

The growing use of EEG in cognitive workload assessment is mostly due to its ability to directly reflect the neural processes involved in attention, perception, memory, decision making and mental effort. EEG differs from subjective questionnaires or behaviour measurement because it provides objective physiological information, which is free from the influence of the participants' opinions or delayed responses

[3]. This has led to the use of EEG monitoring systems for real-time cognitive state estimation in various fields, including aviation, healthcare, transportation, military and adaptive learning environments.

Human brain signals are classified into 5 major frequency bands: Delta (δ), Theta (θ), Alpha (α), Beta (β), and Gamma (γ) [13]. Major differences between Delta waves and Theta waves relate to deep sleep and memory encoding and sustained attention, respectively. Alpha rhythms are typically associated with periods of relaxed wakefulness and decreased mental activity, whereas Beta activity is associated with periods of increased mental activity, such as periods of active thinking, concentration, and problem solving. Higher order cognitive processing and information integration is usually related to gamma oscillations.

Some of the earlier studies have found that the difference between Theta and Alpha band activities is a good predictor of cognitive workload. Increased frontal Theta power has been noted as well as a decrease in parietal Alpha power during memory-intensive and attention-demanding tasks, such as those noted in [12]. Such changes in the brain have been extensively used as discriminative biomarkers for workload estimation. With increasing complexity of tasks, the corresponding EEG activity also varies considerably, so that different workload levels can be automatically determined by intelligent computation models.

The positioning of the EEG electrodes is consistent with the internationally accepted standards with the most widely used configuration in cognitive neuroscience research and clinical diagnosis being the International 10–20 Electrode Placement System [2]. This standard provides uniform positioning of electrodes and promotes uniformity of the signal. Each electrode placement is associated with a specific region of the cortex that has to do with a specific cognitive function. Frontal electrodes primarily record executive functions and working memory, central electrodes motor related, parietal electrodes are involved in sensory integration and attention, temporal electrodes are involved in auditory processing and memory, and occipital electrodes are involved in visual processing.

Over the last years, the acquisition system for brain data using EEG has been substantially enhanced with respect to its applicability in non-standard environments, such as the field. The OpenBCI Cyton board is a portable EEG device that allows for continuous brain signal recording and can be used in immersive Virtual Reality (VR) environments, enabling participants to interact freely with the VR space while their brain signals are being recorded [19]. Portable acquisition platforms overcome the limitations of traditional clinical EEG systems by offering increased flexibility, reduced cost, enhanced usability and without materially compromising EEG signal quality for real-world applications.

While the EEG is a valuable tool for obtaining neurophysiological information, the raw EEG recording is very sensitive to a range of noise and artefacts such as eye blinks, muscle activity, body movements, and environmental interference. Thus, a good preprocessing pipeline is crucial in order to use machine learning or deep learning algorithms. The typical preprocessing procedures include band-pass filtering, artefact rejection, segmentation, normalization and feature preparation, which are effective to enhance the quality of the signals and the discriminative property of the EEG signals (see [welch1967use](#), [oon2018analysis](#)).

Deep learning has been successfully applied in automatic EEG signal analysis in recent years. Deep learning models automatically learn the hierarchical feature representation directly from EEG signals without having to manually craft the features, while traditional machine learning methods require a large number of handcrafted features. The performance of cognitive workload classification has been enhanced with the effective capture of both spatial and temporal characteristics of EEG signals through the use of different architectures, including EEGNet [17], Convolutional Neural Networks (CNNs) [20], Long Short-Term Memory (LSTM) networks [16], Graph Neural Networks (GNNs), and Transformer-based models. It has become a common practice to use EEG as one of the most reliable physiological modalities for assessing the cognitive workload of intelligent tasks.

1.1 Cognitive Workload Assessment using EEG

One of the most commonly used non-invasive neurophysiological tools for monitoring brain activity is electroencephalography (EEG), which has become a critical tool for cognitive workload assessment. EEG has high temporal resolution, and enables the analysis of rapid changes in brain function during cognitive processing, via electrodes positioned on the scalp [10, 11]. EEG has been widely used in neuroscience, brain–computer interfaces (BCIs), neuroergonomics and intelligent human–computer interaction systems due to its real-time monitoring capabilities of neural activities. The growing use of EEG in cognitive workload assessment is mostly due to its ability to directly reflect the neural processes involved in attention, perception, memory, decision making and mental effort. EEG differs from subjective questionnaires or behaviour measurement because it provides objective physiological information, which is free from the influence of the participants’ opinions or delayed responses [3]. This has led to the use of EEG monitoring systems for real-time cognitive state estimation in various fields, including aviation, healthcare, transportation, military and adaptive learning environments. Human brain signals are classified into 5 major frequency bands: Delta (δ), Theta (θ), Alpha (α), Beta (β), and Gamma (γ) [13]. Major differences between Delta waves and Theta waves re-

late to deep sleep and memory encoding and sustained attention, respectively. Alpha rhythms are typically associated with periods of relaxed wakefulness and decreased mental activity, whereas Beta activity is associated with periods of increased mental activity, such as periods of active thinking, concentration, and problem solving. Higher order cognitive processing and information integration is usually related to gamma oscillations. Some of the earlier studies have found that the difference between Theta and Alpha band activities is a good predictor of cognitive workload. Increased frontal Theta power has been noted as well as a decrease in parietal Alpha power during memory-intensive and attention-demanding tasks, such as those noted in [12]. Such changes in the brain have been extensively used as discriminative biomarkers for workload estimation. With increasing complexity of tasks, the corresponding EEG activity also varies considerably, so that different workload levels can be automatically determined by intelligent computation models.

Table 1.1: Five Classifications of Frequency Waves of EEG Signal [3]

Wave	Amplitude Voltage	Frequency Band	Location of Origin	Occurrence
Delta (δ)	70–100 μ V	0.5–4 Hz	Subcortical origin	Brain activity of infants, deep sleep in adults, and severe brain disorders.
Theta (θ)	Around 50 μ V	4–8 Hz	Thalamic and parietotemporal regions	Early sleep, childhood development, and emotional stress in adults.
Alpha (α)	20–60 μ V	8–13 Hz	Occipital region	Awake, relaxed state with eyes closed.
Beta (β)	10–15 μ V	13–30 Hz	Central frontal region	Active thinking, concentration, problem solving, and stress.
Gamma (γ)	Around 10 μ V	> 30 Hz	Distributed cortical regions	Higher cognitive processing, perception, learning, and information integration.

The positioning of the EEG electrodes is consistent with the internationally accepted standards with the most widely used configuration in cognitive neuroscience research and clinical diagnosis being the International 10–20 Electrode Placement System [2]. This standard provides uniform positioning of electrodes and promotes uniformity of the signal. Each electrode placement is associated with a specific region of the cortex that has to do with a specific cognitive function. Frontal electrodes primarily record executive functions and working memory, central electrodes motor related, parietal electrodes are involved in sensory integration and attention,

temporal electrodes are involved in auditory processing and memory, and occipital electrodes are involved in visual processing. Over the last years, the acquisition system for brain data using EEG has been substantially enhanced with respect to its applicability in non-standard environments, such as the field. The OpenBCI Cyton board is a portable EEG device that allows for continuous brain signal recording and can be used in immersive Virtual Reality (VR) environments, enabling participants to interact freely with the VR space while their brain signals are being recorded [19]. Portable acquisition platforms overcome the limitations of traditional clinical EEG systems by offering increased flexibility, reduced cost, enhanced usability and without materially compromising EEG signal quality for real-world applications.

While the EEG is a valuable tool for obtaining neurophysiological information, the raw EEG recording is very sensitive to a range of noise and artefacts such as eye blinks, muscle activity, body movements, and environmental interference. Thus, a good preprocessing pipeline is crucial in order to use machine learning or deep learning algorithms. The typical preprocessing procedures include band-pass filtering, artefact rejection, segmentation, normalization and feature preparation, which are effective to enhance the quality of the signals and the discriminative property of the EEG signals (see [welch1967use](#), [oon2018analysis](#)). Deep learning has been successfully applied in automatic EEG signal analysis in recent years. Deep learning models automatically learn the hierarchical feature representation directly from EEG signals without having to manually craft the features, while traditional machine learning methods require a large number of handcrafted features. The performance of cognitive workload classification has been enhanced with the effective capture of both spatial and temporal characteristics of EEG signals through the use of different architectures, including EEGNet [17], Convolutional Neural Networks (CNNs) [20], Long Short-Term Memory (LSTM) networks [16], Graph Neural Networks (GNNs), and Transformer-based models. It has become a common practice to use EEG as one of the most reliable physiological modalities for assessing the cognitive workload of intelligent tasks.

The human brain is divided into four major lobes, namely frontal lobe, parietal lobe, temporal lobe and occipital lobe, and each lobe is responsible for different cognitive function in mental workload assessment. EEG signals obtained from these cortical areas contain important information about neural processing of attention, memory, decision making and perception. The anterior part of the brain, the frontal lobe, is responsible for more functions, such as executive functions, working memory, concentration, and decision making, where it shows more activation during cognitively demanding tasks [10]. The temporal lobe plays a key role in auditory perception, language comprehension and memory formation, while the parietal lobe is involved

in sensory integration, spatial orientation and attention processing. The occipital lobe is located in the back of the brain and primarily involved with visual processing and visual attention. In order to understand the participant's cognitive state in the execution of the task, multifactorial analysis of the brain lobe signals can be performed by analyzing signals from different brain lobes, as cognitive workload activates multiple cortical regions at the same time [1].

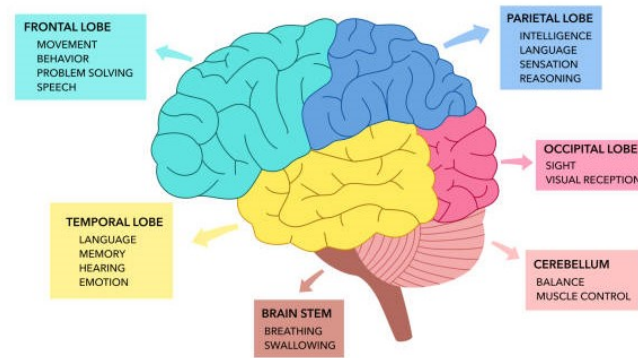


Fig. 1.1: Lobes of the human brain [1].

Fig. 1.1 shows the major functional lobes of the human brain that are involved in cognitive processing.

Electrodes are placed based on the standard electrode placement protocol used in neuroscience research and clinical applications called the International 10–20 Electrode Placement System [2]. In this standardised marking, the labels refer to specific areas of the brain: F = frontal lobe; C = central region; P = parietal lobe; T = temporal lobe; O = occipital lobe and Z = the centre of the scalp. Odd numbered electrodes are used on the left hemisphere, and even numbered electrodes, on the right hemisphere. A number of electrodes are commonly used for recording neural activity from each of the respective brain regions: F3/ F4 for the frontal lobe; C3/ C4 for the central lobe; P3/ P4 for the parietal lobe; T7/ T8 for the temporal lobe; and O1/ O2 for the occipital lobe. Midline electrodes (Fz, Cz, and Pz) also provide information about bilateral brain activity. The standardized electrode configuration is helpful for obtaining consistent signals, enhancing signal uniformity between participants and enabling reliable classification of cognitive workloads with EEG signals [2].

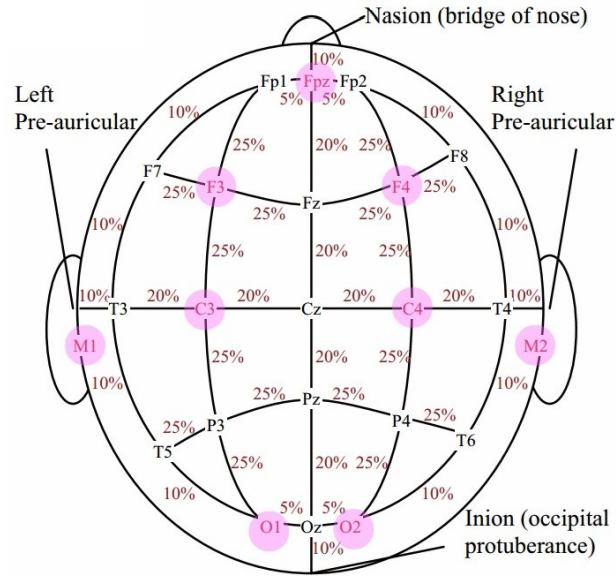


Fig. 1.2: 10–20 EEG electrode placement system [2].

The International 10–20 EEG Electrode Placement System for acquiring EEG signals is shown in figure 1.2. In recent years, EEG has proven to be successful for cognitive workload assessment in a variety of practical applications, such as aviation, transportation, healthcare, and military operations, among others, including education and intelligent human–computer interaction systems [8]. Portable EEG acquisition devices like the OpenBCI Cyton board have made it possible to track brain activity in real time, even in settings that go beyond the laboratory where continuous monitoring previously wasn’t feasible [19]. Further, EEG signals such as Theta, Alpha and Beta rhythms have been widely employed to determine various mental workload, attention, fatigue and cognitive effort states. The physiological signals have also helped to evolve adaptive intelligent systems that can dynamically adapt to users’ cognitive state [16, 17].

1.2 Virtual Reality-based Assessment of Cognitive Workload

Virtual Reality (VR) has become an excellent tool for studying human cognition due to its high level of immersion, interactivity, and control in experimental environments. VR offers a more realistic way of conducting experiments while still being able to control all of the experimental conditions; this is a great benefit compared to traditional lab experiments to assess cognitive workload [5]. The main benefit of Virtual Reality is that it can be used to produce lifelike environments that are essentially the same as real scenarios. Participants engage with virtual objects

and environments in a natural way, enabling researchers to examine the cognitive behaviour under conditions that closely simulate practical applications, and provide repeatable and consistent experiments [7]. VR has been the subject of much interest in recent years in neuroscience, medical applications, education, military training, industrial automation and human–computer interaction. The studies cited have been able to leverage the immersive nature of VR environments to examine various aspects of attention, learning, memory, decision making, situational awareness, and cognitive workload in controlled experimental environments. Previous studies have shown that immersive VR environments can be used to study aspects of attention, learning, memory, decision making, situational awareness, and cognitive workload in controlled experimental settings [6]. VR experiments offer an increased ecological validity as compared with the traditional computer-based experiments because of the sense of presence and engagement that occurs in the virtual world [7].

Previous studies have shown that complexity of the tasks, level of visual input, the complexity of the interactions and decisions required can induce various levels of cognitive workload in Virtual Reality environments [14]. VR is therefore a promising tool for capturing physiological signals (e.g., EEG) during realistic cognitive tasks, allowing researchers to explore brain activity when humans engage in natural interactions, instead of simplified laboratory paradigms. In recent years, advances in consumer Virtual Reality hardware have continued to drive research in this area even further. VR headsets like the Meta Quest 2, which are standalone and don't require any external computing equipment, offer high-resolution graphics, motion tracking, and wireless interaction, enabling participants to perform cognitive tasks comfortably without the need for external computing devices. The technological advances have made it easier to combine VR with physiological signal acquisition systems to monitor cognitive state on the fly. This research aims to use VR as the experimental platform to induce various level of cognitive workload via an immersive memory-based game that was developed with Unity. The VR game itself has 4 workload conditions: Relaxation, Easy, Medium, and Hard; the difficulty level is gradually increased by adding extra memory objects and cognitive challenges. In-game, subjects wear the Meta Quest 2 VR headset with OpenBCI Cyton 8-channel EEG acquisition system simultaneously measuring brain activity. This is a synchronous VR/EEG system that allows for the acquisition of labelled EEG data as a function of cognitive workload during this immersive experimental setup. There are a number of benefits of the VR-EEG integration over traditional measures of workload. First, it allows to conduct realistic cognitive experiments of high ecological validity. Second, it provides a way to monitor the physiology of participants continuously without disrupting their interaction with each other. Lastly, it creates

annotated datasets that are well suited for creating intelligent deep learning models that are effective in automatically estimating cognitive workload in real-world applications.

1.3 Brain-Computer Interface (BCI)

Brain-Computer Interface (BCI): A communication system that allows direct communication between the human brain and an external device that bypasses the normal body neuromuscular pathways. BCI systems record brain signals, analyze them, and interpret the resulting information into instructions for computers, robotic equipment or other electronic systems. This technology has received a lot of attention in neuroscience, healthcare, rehabilitation and human computer interaction, as it allows digital systems to be controlled by the human brain without any physical contact [21, 22]. The most commonly used method of signal acquisition in non-invasive BCI is electroencephalography (EEG) because it is safe, portable, inexpensive and has excellent temporal resolution. EEG-Based BCIs measure electrical activity from the brain using electrodes on the scalp and process the data into useful information through signal processing and machine learning algorithms. These systems have been successfully applied in cognitive assessment, motor imagery, attention monitoring, fatigue detection, neurorehabilitation and assistive technologies for people with physical impairment [10, 11].

With the development of AI and deep learning, the performance of EEG-based BCI systems has been greatly improved. In deep learning models, meaningful representations are learned directly from the EEG signal, and they don't need a lot of manual engineering. This has enhanced the ability to recognize cognitive states and facilitated the creation of intelligent systems for real-time brain signal analysis [9, 16]. The proposed VR-EEG system is designed as the EEG-based Brain-Computer Interface and continuously records brain activity while the participants are performing memory-based tasks in the immersive Virtual Reality environment. The acquired EEG signals are then processed using machine learning to estimate the cognitive workload and memory performance, providing an objective evaluation by combining physiological brain responses with behavioral performance metrics. This combination shows the potential of BCI technology for the development of an intelligent and engaging cognitive assessment system.

1.4 Existing Solutions

For decades, cognitive workload has been the subject of extensive research and many methods have been suggested that estimate cognitive workload based on the person's

mental state during task execution. The current solutions include subjective assessment methods, behavioural performance measures, assessments based on physiological signals and artificial intelligence that relies on classification techniques. All the approaches have their own merits, but they cannot be used as a standalone solution for continuous real-time cognitive workload monitoring [3]. The familiar, easy-to-implement, subjective methods of cognitive workload evaluation are the most widely used methods. The Subjective Workload Assessment Technique (SWAT) and the National Aeronautics and Space Administration Task Load Index (NASA-TLX) are commonly used questionnaires that ask the respondent to report on his or her self-assessment of workload after a task. These methods are low cost and easy to use, but they are highly subjective and subjective, and cannot be used to continuously monitor them in real time, so they are not applicable for continuous real-time monitoring [3]. Reliability of cognitive workload estimates is achieved with behavioural assessment techniques, which use task performance measures like reaction time, task completion time, response accuracy, error rate, eye movements, and keyboard and mouse movements. The above methods measure mental workload indirectly, but they are greatly affected by task type, participant experience, motivation, and environmental factors. This means that behaviour cannot always be used to accurately describe the underlying cognition of an individual [8]. In comparison with other physiological modalities, Electroencephalography (EEG) has proved to be one of the most reliable techniques because it has very high temporal resolution and allows direct measurement of neural activity. The cognitive workload assessment using EEG has shown to be effective in various fields such as; aviation, transportation, medical field, education, military training, and human–computer interaction [10, 11].

Much of the existing research has focused on using traditional machine learning classifications for EEG workload classification. After the extraction of handcrafted features such as statistical, temporal, spectral and wavelet features, promising techniques such as Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Decision Tree (DT), Random Forest (RF) and Artificial Neural Networks (ANN) have been tested. These methods, however, are highly dependent on manual feature engineering and tend to perform inadequately on a different subject, as the physiological variability between subjects can affect their generalization ability [15, 22]. With the recent developments of deep learning, automatic cognitive workload assessment is now much more advanced, and no longer requires hand-crafted features. Deep learning models automatically learn the hierarchy of feature representations directly from raw or minimally-preprocessed EEG signals. Convolutional Neural Networks (CNNs), EEGNet, Recurrent Neural Networks (RNNs), Long Short-Term Memory

(LSTM) networks, Transformers, and Graph Neural Networks (GNNs) have shown remarkable success over traditional machine learning approaches for EEG classification tasks [16, 17, 20]. While there have been significant strides made, there are still a number of challenges to overcome. Several studies already published are based on publicly available EEG datasets acquired under traditional laboratory paradigms (N-back task, mental arithmetic, or visual attention task). These datasets are also typically unecological and do not mimic real-world user interactions in a realistic immersive setting. In addition, some of the current models suffer performance drop under subject independent validation because of the large inter-subject difference among the participants [9, 18]. To overcome these drawbacks, this research suggests a framework to evaluate cognitive workload using EEG signals during playing of an immersive memory game in VR. The proposed system utilizes the Meta Quest 2 VR headset and the OpenBCI Cyton 8-channel EEG acquisition board, which collect brain activity during realistic interactions with virtual environments, instead of traditional cognitive tasks. In addition, two new deep learning architectures are proposed: Multi-Branch Attentive EEGNet (MBA-EEGNet) and Multi-Scale Dynamic Graph Cross-Attention (MS-DGCA) Conformer, which are designed to enhance the performance of cognitive workload classification in the case of subject-independent evaluation settings.

1.5 Objectives

The main purpose of this study is to create an intelligent EEG-based cognitive workload assessment framework that can accurately identify the various cognitive workloads in an immersive VR environment. The proposed system intends to integrate immersive VR technology with state-of-the-art deep learning to realize reliable cognitive workload estimation, independent of the subject.

The aims of this research are:

1. Designing and developing an immersive Virtual Reality memory game that can induce the following controlled cognitive workloads: Relaxation, Easy, Medium, and Hard, for the purposes of controlled EEG data collection [5, 7].
2. To obtain high-quality EEG signals from each player while playing with the OpenBCI Cyton 8-channel EEG acquisition system while playing with the Meta Quest 2 Virtual reality headset [19, 23].
3. Preprocess the recorded EEG signals by using filtering, normalization, segmentation and feature preparation methods to reduce noise and enhance the quality of the recorded signals before classification [24, 25].
4. To build a Multi-Branch Attentive EEGNet (MBA-EEGNet) model that can

learn discriminative spatial features from EEG signals and provide adaptive attention mechanisms for better workload classification [9, 17].

5. To create a Multi-Scale Dynamic Graph Cross-Attention (MS-DGCA) Conformer model that is capable of learning spatial-temporal relationships among the EEG channels, using graph-based feature learning and transformer-based attention mechanisms [16, 18].
6. To test the proposed deep learning architectures with different performance metrics such as classification accuracy, precision, recall, F1 score, confusion matrix analysis, subject-wise evaluation and five-fold cross validation for having a comprehensive view of the models performance [22].
7. To analyze the performance of the proposed architectures and determine the best model to be used in the assessment of the cognitive workload in the context of immersive Virtual Reality environments for multiple classes.
8. To make a contribution to the realization of intelligent real-time cognitive monitoring systems that can aid adaptive learning, health care, transportation, aviation, military training and other human-centred intelligent systems.

1.6 Thesis Organization

The rest of this thesis consists of seven chapters.

Chapter 2: Chapter 2 contains the Literature Review, which outlines the previous studies pertaining to cognitive workload assessment, EEG signal analysis, VR applications and workload classification using deep learning techniques.

Chapter 3: In Chapter 3, the authors discuss the Design and Methodology of the proposed system, experimental setup, development of virtual reality game, EEG acquisition process, EEG preprocessing techniques, dataset preparation, and proposed deep learning architectures.

Chapter 4: Chapter 4 introduces the Implementation details of the proposed framework such as model development, training strategy, software tools, hardware configuration and implementation environment.

Chapter 5: The Results and Discussion of the proposed architectures are discussed in Chapter 5 where the performance of each architecture is compared using various performance metrics such as accuracy for each subject, the confusion matrix analysis, five-fold cross validation and comparative performance evaluation.

Chapter 6: The research ends with a chapter 6 that summarizes the key findings and contributions of the proposed research.

Chapter 7: Chapter 7 covers the weaknesses of the current research and suggestions for Future Work to enhance the EEG-based cognitive workload assessment systems.

Chapter 2

Literature Review

With the rapid development of the Virtual Reality (VR), Electroencephalography (EEG), and Brain-Computer Interface (BCI) technologies, the field of cognitive assessment has undergone a significant transformation. Traditional cognitive assessment tools are mostly questionnaires, paper tests, and behavioral assessments, and they may yield subjective findings and only a superficial understanding of the underlying neural mechanisms. To date, scientists are putting immense effort into developing methods that combine immersive virtual environments with physiological signal analysis to provide more objective and reliable measures of cognitive function, and these techniques are growing in popularity. Over the past few years, researchers have introduced more and more methods combining the immersive virtual environment with physiological signal analysis, to provide more objective and reliable measures of cognitive function, and these methods are gaining increasing popularity. EEG is one of the most popular non-invasive methods of recording brain activity during cognitive tasks due to its high temporal resolution and its ability to provide real-time brain responses. Meanwhile, Virtual Reality has become an effective platform for creating interactive and immersive assessment settings to enhance participant understanding and experimental realism. These technologies have now opened up new avenues for the development of smart cognitive assessment systems that integrate behavioral measures and neural activity [9, 10].

In recent years, several machine learning and deep learning approaches to the analysis of EEG signals recorded during cognitive activities have been put forward. Various classical machine learning methods such as Support Vector Machines (SVM), Random Forest (RF) and K-Nearest Neighbors (KNN) have been found to be suitable for cognitive workload classification. In recent years, deep learning architectures like EEGNet, CNN-LSTM, and Transformer-based models have been developed to further enhance classification accuracy by automatically learning complex spatio-temporal patterns in EEG signals, while avoiding complex manual feature engineering [11, 16]. Significant strides have been made but there are still some challenges to address. There are already a lot of studies assessing cognitive performance with either EEG signals or Virtual Reality. EEG based approaches are usually based on laboratory experiments and the level of interaction is limited, while VR based approaches are often based only on behavioral measures without physiological brain responses. Moreover, the variability in datasets, feature extraction

procedures, experimental design and model architectures complicates a direct comparison of existing methods and identification of the most appropriate framework to apply to real cognitive assessment.

Hence, the literature available on EEG based cognitive assessment, Virtual Reality applications, Brain-Computer Interface technologies, deep learning approaches and recent integration frameworks are reviewed in this chapter. The reviewed studies provided the theoretical basis for this research, limitations in the current studies and the need for the proposed VR-EEG System for Gamified Assessment.

2.1 Existing Techniques and Their Limitations

The following sections will review the current techniques available and their limitations. There are many methods published that are proposed to assess cognitive workload based on Electroencephalography (EEG) signals. Previous research mainly focused on the use of classic machine learning algorithms such as K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF) and Support Vector Machine (SVM). Most of these approaches are based on manually extracted statistical, temporal, or spectral features from preprocessed EEG signals. Their value is yet to be proven under real-world conditions, and they are heavily relying on the quality of handcrafted features and intensive preprocessing steps [3, 11]. The recent rapid progress in deep learning has driven the research transition to automatic feature learning methods for obtaining complex spatial and temporal information directly from the EEG. CNNs have been applied to learn spatial representations, and Long Short-Term Memory (LSTM) networks have demonstrated good results in building temporal models from EEG signals. In addition, hybrid CNN-LSTM networks are proposed to take advantage of both spatial and temporal information in brain activity for enhancing the classification accuracy, as in [16, 17].

In recent years, attention-based models, such as Transformer-based architectures and Conformer models, have gained a significant focus due to their ability to model long-range dependencies in EEG signals by leveraging self-attention mechanisms. These models have shown to be more efficient in the task of cognitive workload estimation and EEG classification when compared with traditional deep learning models. They still, however, tend to require more massive training sets and more computational power than others, which makes them less practical for real-time applications [9, 18]. Although great strides have been made using the current methods, there are some drawbacks. Many studies test them with small number of data points that are taken in controlled laboratory environments, and thereby limit the generalizability of the proposed methods. Besides, current methods are mostly based on EEG

analysis without considering immersive environments like Virtual Reality. User engagements are therefore often restricted and behavioral information which may be utilized for cognitive assessment is not properly harnessed [10, 22]. Another drawback is the fact that many cognitive assessment systems are based on neural signals and do not take into consideration other complementary behavioural measures like reaction time, task accuracy, and task completion time. These behavioural measures, combined with brain activity, can give a more holistic picture of cognitive performance. In this context, recent research has focused on multimodal cognitive assessment framework using EEG and Virtual Reality and high-level deep learning algorithms to enhance the assessment accuracy and user experience. The proposed VR-EEG System for Gamified Assessment is along this new research horizon, implementing Virtual Reality (VR) based memory tasks and real-time EEG acquisition. The proposed framework is able to correlate the neural activity with the behavioral performance, thus offering a more objective assessment of memory performance and cognitive workload than traditional EEG-based assessment systems.

2.1.1 Traditional Machine Learning Approaches

The classic machine learning approaches are currently employed. The traditional machine learning approaches are currently used. The traditional machine learning-based approaches have been widely applied in cognitive workload evaluation from EEG data due to their relatively simple implementation and low computation requirements. The common methods are mostly a series of preprocessing procedures such as noise removal, feature extraction, feature selection and classification. The quality of the extracted features is a crucial factor for the performance of the classification model. These are typically statistical measures, power spectral density (PSD), wavelet coefficients, entropy and frequency band energies derived from electroencephalograms (EEGs) (cf. [3, 10]). In the conventional machine learning algorithms, Support Vector Machine (SVM) has been one of the most commonly used classifiers because it is effective in dealing with the high dimensional EEG signal. Some studies have already shown the satisfactory performance of SVM in distinguishing subjects and classifying cognitive workloads and mental states. On the other hand, Random Forest (RF) has been found to be very successful for classification due to its ensemble learning approach, similar to K-Nearest Neighbors (KNN) and Decision Tree (DT) classifiers, which have been used in various cognitive assessment tasks based on EEG signals [11, 13].

Although traditional machine learning methods are effective, they have a number of drawbacks. They highly rely on handcrafted feature extraction, which demands a considerable amount of domain knowledge and signal preprocessing. Moreover,

manually extracted features can miss out the complex spatial and temporal relationships in EEG recordings. However, the accuracy of using traditional machine learning techniques often drops dramatically when dealing with large datasets or real-world cognitive evaluation conditions with noisy physiological data [17, 22]. While traditional machine learning algorithms are still useful, due to their computational efficiency and interpretability, recent work has increasingly focused on deep learning approaches that are capable of learning discriminative representations directly from EEG signals without any other prior training. These models learn to classify with high accuracy on different cognitive assessment tasks without relying on hand-crafted features.

2.1.2 Deep Learning Approaches

The current trend of collecting a large number of EEG signals and the rising power of available computing devices has boosted the use of deep learning methods for the measurement of cognitive workload. Deep learning models learn hierarchical representations directly from EEG signals without relying on handcrafted features as standard machine learning models do. This capability allows them to better capture complex spatial and temporal relationships in neural data, leading to better classification results and less reliance on handcrafted features [16, 17]. Convolutional neural networks (CNNs) are one of the most popular deep learning modalities used for EEG signal processing. CNNs learn local spatial patterns from the EEG recording with the help of convolutional filters and by minimizing manual feature engineering. They have proven to be very useful in applications like cognitive workload estimation, emotion recognition, seizure detection and brain-computer interface systems due to their capability to automatically identify discriminative features. However, conventional CNN models mainly focus on spatial information and may not fully capture the temporal dynamics of EEG signals [10, 17].

In order to solve this problem, Long Short-Term Memory (LSTM) networks have been proposed for sequential EEG analysis. LSTM models are particularly well suited to the task of learning long-term temporal relationships and have shown good results in cognitive state recognition, attention monitoring, and assessment of mental workload. However, LSTM networks might not provide an optimal way to learn spatial correlations among EEG channels, especially in multi-channel EEG recordings [11, 16]. In recent years, hybrid architectures incorporating CNN and LSTM are thus gaining popularity. The models use CNN layers to learn the spatial representation of the EEG signals, and LSTM layers to learn the temporal evolution. CNN-LSTM model has been shown to be superior to CNN or LSTM models in several studies, as they are able to utilize spatial and temporal information of the EEG

signal. These models are hybrid approaches that have yielded promising results in cognitive workload estimation, fatigue detection, and memory assessment tasks, such as [9, 16].

In recent years, attention-based deep learning architectures have also been investigated, such as Transformers and Conformers. These models use self-attention to establish connections between remote EEG channels and time segments to learn features more effectively than traditional recurrent networks. While these structures can often yield high classification rates, they typically demand extensive data sets, computational power, and training periods, complicating their practical application in resource-constrained cognitive evaluation systems like those used in portable or lightweight devices [9, 18]. In summary, deep learning has made significant strides in the field of EEG-based cognitive assessment, enhancing classification accuracy and minimizing the amount of manual feature engineering. But there are still some challenges on the horizon, such as model complexity, computational costs, reliance on the data set, and cross-subject generalization. Therefore, for real-world applications, researchers are still working on the efficient hybrid architectures to achieve high performance with computational efficiency.

2.1.3 Hybrid Deep Learning Models

In recent times, studies have demonstrated that hybrid deep learning models can effectively capitalise upon the advantages of each neural network architecture in the same model, thereby addressing the limitations of each single architecture. Combining more than one learning mechanism, hybrid models can make use of complementary information in the EEG signal. They have shown great performance in cognitive workload estimation, emotion recognition, motor imagery classification and brain-computer interface applications [16, 17]. A popular hybrid network is the fusion of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. In this architecture, CNN layers automatically learn spatial features from multi-channel EEG recordings, and LSTM layers learn temporal dependencies that exist in the sequential brain signals. The combination of these two models allows for better representation of features, resulting in better classification accuracy than using a CNN or LSTM alone [9, 16].

Recently, researchers have added attention mechanisms to hybrid deep learning architectures to further enhance feature representation. Self-attention allows the models to determine the best EEG channels and time intervals to use for the most informative information and to ignore the redundant information. This concept has been further expanded by Transformer based and Conformer based architectures which fuse the self-attention layers into the convolutional architecture, enabling learning

of both local and global EEG patterns. Such models have demonstrated promising results in various EEG classification applications, such as cognitive workload assessment and mental state recognition [9, 18]. Although hybrid deep learning models have achieved good results, there are still some practical problems to be solved. They typically need more training time, larger amount of labeled data, and more computing resources than traditional machine learning techniques due to their complex designs. In addition, the vast majority of previous work has tested such models in laboratory settings with small numbers of subjects, making it difficult to extrapolate these to other users and experimental scenarios. Thus, the robustness and cross-subject generalization of models are an ongoing research effort. The proposed research uses deep learning to analyze EEG signals from immersive Virtual Reality memory tasks. Combining neural activity and behavioral performance allows for a more holistic evaluation of cognitive workload, while taking advantage of the ability of modern hybrid deep learning architectures to perform feature learning.

2.1.4 Existing Challenges

While great advances have been made in the field of EEG-based cognitive evaluation, there are still some problems that hinder the use and effectiveness of the current systems. One of the major challenges is the poor signal quality of EEG recordings. EEG signals are very sensitive to artefacts from eye blinks, muscle activity, head movements, and environmental electrical noise. The presence of these unwanted components usually degrade the signal-to-noise ratio and negatively impact the performance of machine learning and deep learning models. Thus, it is crucial that the preprocessing and artifact removal stages be done efficiently before performing reliable cognitive analysis [3, 10]. Another important challenge is the considerable variability of EEG signals among different individuals. Brain activity is not the same among different age groups, different mental states, different levels of fatigue and different individuals' physiology, making it difficult to develop a generalizable model for different subjects. As a result, many of the current models achieve high accuracy on test sets of subjects from a particular distribution but suffer from a significant drop in performance on test sets with different subject distributions [17, 22].

Another important issue that is relevant to EEG research is the availability of datasets. The majority of EEG data publicly available are relatively small and collected in laboratory settings with strict experimental controls. This may not reflect cognitive activities in the real world, restricting the robustness and practical use of the models developed. Moreover, the data collection of high quality EEG signals is time-consuming and resource-consuming as it requires specialized equipment, controlled experimental protocols, and expert supervision [11, 16]. Recently, the deep learning

architecture has been enhanced with CNN-LSTM, Transformers, and Conformers, which have greatly improved the classification accuracy from a computational point of view. But such models tend to be resource-intensive, slow to train, and need a large set of annotated data. Using them in portable or real-time cognitive assessment systems then remains a challenge, especially when speed and efficient resource usage are required as in inception [9, 18].

Another drawback that is found in the literature is a lack of integration of immersive technologies and physiological monitoring. Numerous studies emphasize only on analyzing the EEG data or assessing cognitive performance through Virtual Reality without taking objective neural data into account. Consequently, there are important relationships between behavioural performance and underlying brain activity that are not captured. The combination of EEG and Immersive Virtual Reality environments can offer a more holistic view of cognitive processes, by examining both physiological responses and user actions in real time. The VR-EEG System for Gamified Assessment aims to solve these research problems through a combination of immersive Virtual Reality (VR), EEG brain monitoring, and innovative deep learning algorithms. The proposed framework uses both neural activity and behavioral performance measures (reaction time, task accuracy, and task completion time) to achieve more reliable and objective measurements of cognitive workload and memory performance.

2.2 Electroencephalography (EEG) in Cognitive Assessment

EEG is now one of the most popular non-invasive methods to study brain activity during cognitive processing. It measures the electricity produced by the neurons in the cortex using electrodes attached to the scalp, giving information in real time on neural activity related to attention, memory, perception and decision-making. EEG is a valuable technique in neuroscience research, clinical diagnosis and brain computer interfaces because of its high temporal resolution, relatively low cost and portability. It is also very well suited for cognitive assessments that require continuous monitoring of the brain's activity while individuals are engaged in varying mental tasks [10, 11]. EEG obtains physiological data about brain function in contrast to traditional assessment approaches which primarily depend on behavioural observations or questionnaires. By examining the variations in EEG activities, researchers can better assess cognitive states, such as cognitive workload, mental fatigue, attention level, and memory performance. EEG is directly recording the neural response, so it has been widely used in memory assessment, learning performance, emotion detection, fatigue detection and workload estimation studies.

In most instances, EEG signals are processed into various frequency bands: Delta, Theta, Alpha, Beta and Gamma, which correspond to different facets of brain activity. Of these, Theta, Alpha and Beta rhythms are of special importance in cognitive assessment as they are closely linked to memory processing, attention, concentration and mental workload. Increased frontal Theta activity and changes in Alpha and Beta power have been often reported during demanding cognitive tasks reflecting greater mental effort and information processing [3, 13]. But, with the advancements in signal processing and artificial intelligence, EEG-based cognitive assessment systems have been expanded further. Today's deep learning methods extract temporal and spatial models automatically from the EEG signals instead of relying on handcrafted features, which results in better cognitive state classification accuracy. These developments have helped EEG to make an important contribution to intelligent healthcare systems, adaptive learning environments, neurorehabilitation and immersive Brain-Computer Interface applications.

EEG is the main physiological sensing used as a tool for observing users during memory-based tasks in a Virtual Reality environment with the proposed research. The proposed system will use EEG signals to measure neural activity along with cognitive workload and behavioral performance to give a more objective assessment of memory performance and workload than current assessment techniques.

2.2.1 EEG Frequency Bands

There are different frequency bands of EEG signals based on their oscillatory properties. Every frequency band has a specific pattern of neural activity, and is linked to different cognitive and physiological functions. The five major EEG frequency bands include Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), and Gamma (>30 Hz). This is because these bands can give clues to various mental conditions, from deep sleep to complex mental activity, such as [10, 13].

Of these frequency bands, Theta, Alpha, and Beta are of special significance when it comes to assessing cognitive function. Theta is normally higher when remembering, when someone is focused on a task or when their brain is working hard. Alpha activity is typically linked to relaxation and less visual awareness while Beta is typically associated with active thinking, concentration, decision making and problem solving. The changes in these frequency bands have been widely applied to assess cognitive workload, memory and learning behaviour in healthy subjects and clinical groups, as reported in the literature under the name ARFNs [3, 9]. The cognitive workload studies mainly focus on Theta, Alpha and Beta bands since they have been found to show significant changes in memory-based and attention demanding tasks, although Gamma waves have been found to be associated with higher order cog-

nitive functions like perception and information integration. For this reason, these three frequency bands are chosen to be associated to the estimation of the users' cognitive workload when performing memory based activities in the proposed VR-EEG system.

The characteristics of the major frequency bands of EEG commonly found in the literature are summarized in figures 2.1.

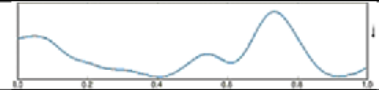
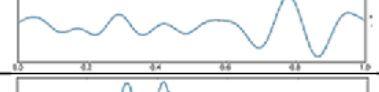
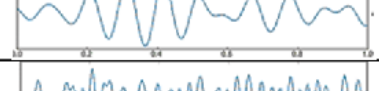
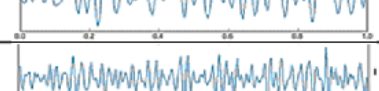
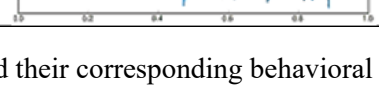
Waves	Frequency bands (Hz)	Behaviour Trait	Signal Waveform
Delta	0.3 – 4	Deep sleep	
Theta	4 – 8	Deep Meditation	
Alpha	8 – 13	Eyes closed, awake	
Beta	13 – 30	Eyes opened, thinking	
Gamma	30 and above	Unifying consciousness	

Fig. 2.1: Classification of EEG frequency bands and their corresponding behavioral characteristics.

[25]

EEG signals frequently contain several kinds of noise and artifacts produced by eye blinking, muscle motions, power-line interference and electrode movements. Thus, pre-processing the signal is crucial prior to gaining useful information for cognitive evaluation. The aim of preprocessing is to enhance the signal quality while maintaining neural information that corresponds to cognitive activity [10, 11].

EEG preprocessing typically includes band pass filtering, artifact removal, signal normalization, and segmentation. Low-frequency drift and high-frequency noise are typically filtered out with band-pass filters, and artifact removal techniques are employed to remove unwanted high-frequency components generated by eye movements and muscle activity. The continuous EEG signals are then segmented into windows of smaller duration for feature extraction and further analysis [13, 16].

After the preprocessing, features are extracted from the EEG signals for characterization of the brain activity. In recent years, the traditional feature extraction methods and deep learning methods have all been widely used. Deep learning-based models automatically learn hierarchical representations from the EEG signals without requiring traditional methods to compute statistical or spectral features. This capa-

bility has greatly enhanced the performance of cognitive assessment systems based on EEG and decreased manual feature engineering requirements [9, 18].

2.2.2 EEG-Based Cognitive Assessment

EEG is one of the most effective physiological methods for the assessment of cognitive functions since it is directly linked to brain activity involved in cognitive processing. EEG is unlike traditional assessment techniques, which are mainly behavioral and subjective questionnaires, as it enables ongoing assessments of brain activity and real-time objective assessment of cognitive states. This has rendered EEG a valuable tool to examine attention, working memory, decision making, learning performance and mental workload for both research and clinical purposes [10, 11].

There are several studies that have shown that cognitive workload can be estimated by examining changes in EEG frequency bands during various mental workloads. Research involving memory-based experiments, arithmetic problems, visual search tasks, and tasks involving attention have been demonstrated to have consistent changes across levels of task difficulty in Theta, Alpha, and Beta rhythms. The neural responses are useful in distinguishing various cognitive levels and mental workloads [3, 9].

The effectiveness of EEG-based cognitive assessment has also been enhanced by recent advances in machine learning and deep learning. Handcrafted EEG features have been used to achieve satisfactory results in traditional ML algorithms like Support Vector Machine (SVM), Random Forest (RF) and K-Nearest Neighbors (KNN). Recently, deep learning systems such as EEGNet, CNN-LSTM, and Transformer-based systems have shown that they can learn spatial and temporal representations directly from EEG data, leading to better classification accuracy.[16, 18].

Although these are all great developments, there are some problems to contend with. Signal preprocessing and model generalization are challenging because of the high noise level, motion artifacts, and individual differences of EEG signals. In addition, a large number of existing EEG assessment systems have been created in a controlled laboratory environment and offer minimal interaction with the user. The constraints have inspired researchers to combine EEG with immersive systems like Virtual Reality (VR) to provide more realistic and engaging cognitive assessment scenarios and simultaneously obtain objective measurement of brain activity.

The proposed research takes this route with the goal of incorporating the EEG acquisition with a Virtual Reality memory game. The proposed system uses both neural activity and cognitive metrics derived from the game, such as accuracy, reaction time, and task completion time, to offer a more holistic assessment of cognitive per-

formance and workload.

2.3 Virtual Reality in Cognitive Assessment

Virtual Reality (VR) is a promising technology that can be used to create an immersive and interactive environment that mimics the real world. VR differs from conventional computer application, which is used with screens, in that it enables users to interact naturally with virtual objects and environments using head-mounted displays (HMDs), motion controllers and tracking sensors. VR offers a unique opportunity for cognitive assessment and rehabilitation, as it is an immersive experience that can be used to increase user engagement and allow researchers to have more control over experimental conditions [5, 6, 14].

VR has recently gained popularity in the healthcare industry for physical rehabilitation, neurological therapy, surgical training, pain management, and cognitive assessment in recent years. Realistic environments can be designed to allow clinicians and researchers to assess cognitive functions in an environment with controlled but realistic conditions. VR-based assessment is also more ecologically valid than conventional paper paper and computer-based cognitive tests, as it presents participants with a set of environments that are more representative of real life scenarios[6, 7].

Various research studies have shown that VR can be used to measure cognitive functions like memory, attention, executive function, spatial navigation, and decision-making. Memory-based VR tasks involve participants to search for objects in the virtual space and remember previously learned content. These tasks promote greater participant engagement and yield more detailed behavioural measures such as reaction times, navigation patterns, task completion times and accuracy. These behavioral measures can be used to gain insights into cognitive performance and are frequently used alongside physiological signals for enhanced assessment accuracy [7, 9, 18].

By using VR along with physiological sensing technologies, the potential capabilities of cognitive assessment systems are further enhanced. Scientists have combined VR with wearable sensors and eye tracking with Electroencephalography (EEG) to explore brain activity while engaging in a VR based cognitive task. Researchers have used VR in conjunction with wearable sensors, eye tracking, and the EEG to study brain activity throughout VR-based cognitive tasks. [3, 16].

Although VR-based cognitive assessment systems have several merits, it still has some issues to overcome. While several current systems are based on the behavioral performance only, some others work in highly controlled laboratory setting that restricts their applicability. Moreover, some users can experience discomfort or

cybersickness with long exposure to VR, necessitating careful experimental design and adaptation to the user.

To overcome these challenges, the research proposed here combines a Virtual Reality memory game and EEG monitoring of brain activity. The developed framework can be used for simultaneously collecting behavioral and neural data, which allows for more objective evaluation of memory performance and cognitive workload than traditional memory assessment methods.

2.4 Brain-Computer Interface (BCI)

Brain-Computer Interface (BCI) is a technology that allows the direct communication of the brain with an external device by converting neural activity into meaningful commands. BCI systems are different from the regular methods of interaction based on the muscles or peripheral nerves because they use brain signals to communicate with computers, assistive devices, or other digital applications. This ability has been the subject of considerable interest in neuroscience, rehabilitation, health care, and human-computer interaction, where the accurate, quantifiable monitoring of brain activity is crucial [21, 22].

EEG is the most popular technique for acquiring brain signals among the various ones, being the most portable, easy to use, affordable, and having the highest temporal resolution, which makes it the most suitable for non-invasive BCI systems. The BCIs based on EEG continuously monitor neural activity and use signal processing and machine learning techniques to translate the electrical signals into valuable information. They have been demonstrated as useful tools for motor imagery recognition, cognitive workload estimation, attention monitoring, fatigue detection, emotion recognition and neurorehabilitation [10, 11, 22].

With the recent developments in the field of artificial intelligence, BCI systems have become much more efficient. Previous studies generally used handcrafted features and traditional machine learning algorithms like Support Vector Machine (SVM), Random Forest (RF) and K-Nearest Neighbors (KNN). These methods had good results in a controlled setting, but were not necessarily easily transferable to other subjects and had extensive feature engineering. To overcome these shortcomings, the automatic extraction of complex spatio-temporal representations directly from EEG recordings using modern deep learning architectures such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, EEGNet [17] and Transformer-based models [9, 16] have been developed.

The novel application of BCI in conjunction with Virtual Reality has enabled novel opportunities for the assessment and neurorehabilitation of cognition in an immer-

sive environment. EEG-based BCIs monitor users' cognitive responses continuously during interaction with virtual environments, which offer realistic task scenarios. By integrating behavioral and neural measurements, the proposed approach allows researchers to gain a more holistic view of the cognitive workload, attention, and memory performance than traditional methods do. The proposed method comprehensively assesses cognitive workload, attention and memory performance by combining behavioral performance and neural activity.

Although these developments are promising, there are still a number of challenges in the way of the realization of useful BCI systems. EEG signals are prone to individual variability, electrode displacement, and noise, which makes the acquisition of a reliable signal in the real world challenging. Moreover, many current BCI trials are conducted in highly controlled settings with small number of data sets and experimental procedures, limiting their relevance to real world cognitive testing situations. The above restrictions underscore the importance of the development of efficient and easy-to-use BCI frameworks that are able to perform well in immersive conditions. These challenges are overcome by developing a Brain-Computer Interface with a Virtual Reality memory game for the proposed research. The obtained EEG signals are used in combination with behavioural performance measures for an objective evaluation of memory performance and cognitive workload. The integrated system seeks to enhance the reliability of assessment and user engagement while laying the groundwork for future intelligent cognitive assessment systems.

Table 2.1: Summary of Literature Review

Authors	Technique Used	Key Findings	Limitations	Performance Metrics
Wang et al. [9]	Attention-Based Recurrent Fuzzy Network (ARFN)	Attention mechanism significantly improved EEG-based mental workload assessment by extracting discriminative temporal features.	Validated on limited EEG datasets; computational complexity increases with network size.	90.81%
Chen et al. [18]	Improved InceptionTime Network	Multi-scale temporal convolutions enhanced workload classification compared with conventional CNN models.	Generalization across subjects requires further investigation.	88.79%
Liu et al. [16]	Spatial–Temporal–Spectral Feature Fusion	Fusion of spatial, temporal and spectral EEG features improved robustness and workload prediction.	Higher computational complexity due to multimodal feature extraction.	89.00%
Lawhern et al. [17]	EEGNet	Compact CNN architecture achieved competitive performance while using very few trainable parameters.	Performance decreases on highly complex EEG datasets.	84.00%

Continued on next page

Table 2.1 (Continued)

Authors	Technique Used	Key Findings	Limitations	Performance Metrics
Schirrmester et al. [20]	Deep ConvNet	Deep CNN automatically learned discriminative EEG representations directly from raw signals.	Requires a relatively large training dataset.	84.50%
Bashivan et al. [15]	RCNN (CNN + RNN)	Combined spatial EEG mapping and temporal modelling for cognitive workload recognition.	Requires topographic EEG image generation before classification.	92.00%
Katmah et al. [3]	EEG Signal Processing Review	Comprehensively reviewed EEG preprocessing, feature extraction and classification techniques for mental stress assessment.	Review paper; no experimental classification model.	NR
Lotte et al. [22]	Review of EEG Classification Algorithms	Summarized advances in EEG classification algorithms for Brain-Computer Interface applications.	Review paper; no experimental accuracy reported.	NR
Parsons [7]	Virtual Reality Cognitive Assessment	Demonstrated that immersive VR provides ecologically valid environments for cognitive workload studies.	Focused on VR applications rather than classifier development.	NR
Burdea and Coiffet [5]	Virtual Reality Technology	Established the theoretical foundation of immersive virtual reality systems for research and training.	Book chapter; no workload classification experiment.	NR

2.4.1 Comparative Analysis

As shown in the previous sections, conventional machine learning and deep learning has enabled the remarkable advances in EEG-based cognitive assessment. Some of the traditional machine learning algorithms including Support Vector Machine (SVM), Random Forest (RF) and K-Nearest Neighbors (KNN) have achieved good classification performance after appropriate preparing of the EEG features. They are, however, confined to manually extracting features, which restricts their ability to adapt to complex EEG patterns and large-scale datasets [3, 11]. Many of these have been overcome by deep learning methods which have learned meaningful representations from EEG signals automatically. CNN-LSTM, CNN, EEGNet, LSTM and Conformer have been proven to be useful in capturing spatial and temporal features of EEG signals to recognize cognitive state in architectures. Of these models, hybrid and attention based models performed better at classification accuracy, but they also consume more computational resources and larger annotated data sets, [9, 16, 17].

Another technology that is becoming more important in cognitive assessment is Virtual Reality, which has advantages in providing an immersive and interactive context to enhance engagement and simulate realistic task conditions. However, there are many current VR-based systems that focus mainly on the behaviour of the person and disregard physiological measures of brain activity. As a result, the processes of the underlying cognition during task execution may not be captured in the systems [6, 7]. However, a few EEG-based cognitive assessment research works can estimate mental workload and cognitive performance, but are performed in laboratory settings with static visual tasks or traditional computer interfaces. These experiments do not always have ecological validity and do not always reflect the actual cognitive behaviour in the wild. In addition, many published models suffer from cross-subject variability, signal artifacts and a limited number of data sets, which reduces the reliability and generalizability of the models. Besides, due to cross-subject variability, signal artifacts or limited number of data sets, many published models are not reliable or generalizable.

From the literature studied, it can be concluded that the use of Virtual Reality in combination with the technology of EEG-based Brain-Computer Interface presents a promising trajectory to take future systems of cognitive assessment. Using immersive VR environments alongside physiological brain monitoring provides the opportunity to analyse behavioural and neural responses simultaneously, providing a more comprehensive evaluation of cognitive performance. The proposed VR-EEG System for Gamified Assessment is in this direction, that is, to embed a memory-based VR game into a VR system, with the acquisition of EEG signals and deep learning analysis of the results to obtain objective evaluation of cognitive workload and memory performance.

2.4.2 Research Gap

Based on the literature reviewed in this chapter, it can be seen that significant advances have been made in the development of EEG-based cognitive assessment systems. The automatic analysis of EEG signals has been greatly enhanced by the use of traditional machine learning algorithms and modern deep learning models, which now enable the automatic classification of cognitive workload, attention, and memory-related brain activity. In the same way, VR has shown great promise in creating virtual spaces that increase engagement and enable users to perform real-life thinking tasks. While all these progress have been made, there are still some key research areas that need to be addressed for cognitive assessment systems to be effective and practically applicable. The first drawback found in the literature is the significant number of studies exploring the analysis of EEG signals and VR separately. EEG-based neural signal processing methods are mainly conducted in a controlled lab environment, whereas the VR-based cognitive testing systems usually measure behavioral performance with no brain responses. Therefore, these methods

only offer partial knowledge of an individual's cognitive status, and do not create a complete link between neural activity and behavioral performance [9, 10].

One more constraint is the requirement for many existing deep learning models to rely on large annotated datasets and complex computational procedures. While CNN-LSTM, EEGNet, or Conformer have shown good classification results, there are challenges in their robustness on various subjects and experiments. Furthermore, very few studies have focused on cognitive workload assessment with VR tasks based on memory in an immersive environment, especially in a gamified assessment context as in [16, 17]. In addition, the number of studies published mainly focus on cognitive workload measurement based on EEG signals, with behavioral metrics (reaction time, task completion time and task accuracy) being analyzed separately. Incorporating these complementary sources of information can enhance the reliability and interpretability of cognitive assessment by offering a more comprehensive understanding of user performance.

This thesis suggests an innovative VR-EEG System for Gamified Assessment, which combines immersive Virtual Reality, EEG-based brain activity monitoring, and behavioral performance analysis in a single system to fill these research gaps. The system is designed to measure and evaluate the cognitive workload and memory performance in a more objective and comprehensive manner by accounting for neural responses and user interactions for memory-based VR tasks. The efficiency of the suggested framework is examined by means of sophisticated deep learning methods and experimentally validated by live EEG recordings during an immersive game session.

Chapter 3

Design & Methodology

The entire methodology used for the design of the proposed VR-EEG System for Gamified Cognitive Assessment is described in this chapter. The proposed framework combines an immersive Virtual Reality (VR) environment and Electroencephalography (EEG) signal acquisition to objectively evaluate the cognitive workload and memory performance. The overall methodology involves several steps such as experimental setup, EEGCAN acquisition, signal preprocessing, feature extraction, dataset preparation, deep learning model development, training and evaluation. Participants initially had their EEG data collected while they are using the Virtual Reality environment created with the Meta Quest 2 headset to complete memory related tasks. The EEG data were acquired with OpenBCI Cyton 8 channel biosensing board with gel electrodes. The recorded signals were subsequently preprocessed to eliminate noise and artifacts, and segmented into specific-length windows for deep learning analysis. After preprocessing, frequency band representations were extracted corresponding to Theta, Alpha and Beta rhythms which are known to be closely related to attention, working memory, and cognitive workload. The resulting EEG signals were subsequently sorted into labeled sets of data, based on the different cognitive load levels used during the VR game play.

In this research, three deep learning architectures were designed and tested for automatic cognitive workload classification. The first model is the Multi-Branch Attentive EEGNet (MBA-EEGNet) that extends the original EEGNet (Sharma et al., 2019) by adding multiple parallel feature extraction branches. The second model is the MS-DGCA Conformer which is a Multi-Scale Dynamic Graph Cross-Attention Conformer designed to include both temporal and spatial dependency among EEG channels. A hybrid architecture, termed as MS-DGCA-MBA-EEGNet, was then proposed to combine the best of both architectures in order to get the superior feature learning and classification performance. All of the models suggested were compared based on the classification metrics such as accuracy, precision, recall, F1 score, and confusion matrix analysis. The overall workflow of the proposed VR-EEG cognitive assessment framework is shown in

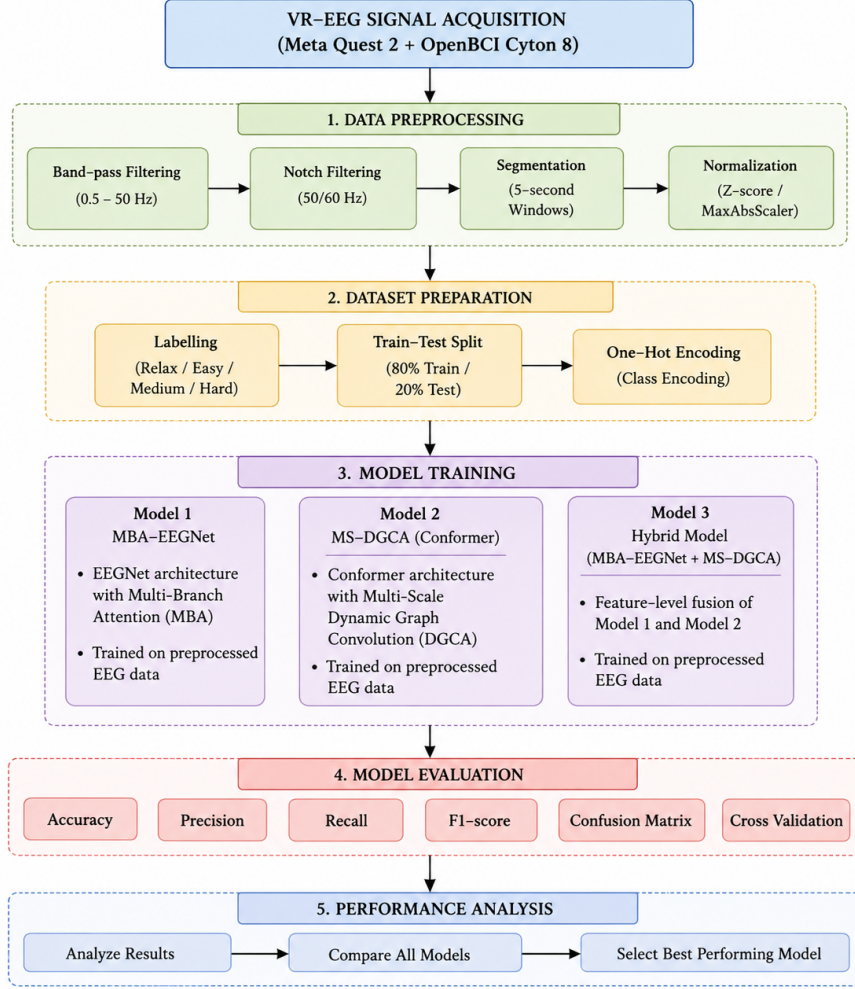


Fig. 3.1: Process Flowchart of VR-EEG Based System For Gamified Assessment

3.1 Dataset Description

The database used in this study has been developed specifically for the proposed system VR-EEG for gamified cognitive assessment. The EEG signals were recorded from healthy subjects while they were engaged in memory-related tasks within a VR space. The goal of the dataset was to record changes in brain activity as they happened during the game at varying cognitive loads. For experimental study, 16 healthy subjects participated voluntarily. Each participant was taken through the procedure and they gave an informed consent before the experiment. The OpenBCI Cyton 8-channel biosensing board was used to continuously collect EEG data, while the participants played the VR memory game with the Meta Quest 2 headset. The experimental protocol comprised four different cognitive conditions, with an ascending mental workload. First, every participant went through a Relaxation phase as a baseline recording. Next, three levels of the game, Easy, Medium and Hard, were played with the participants. The progressive complexity of the tasks was designed to elicit various degrees of cognitive load and working memory load.

EEG signals were acquired at a sampling frequency of 250 Hz, which is considered to be adequate for the study of the neural activity involved in attention, memory processing and cognitive workload. These acquired signals were stored along with the workload labels, and then preprocessed and analyzed using deep learning. For each recording session, then, the EEG data were classified into one of four classes: Reduce the cognitive load on the participant while acquiring the baseline recording. Minimize the cognitive load on the participant during baseline recording.

- Easy: Low cognitive load for VR memory task.
- Medium: Requires more concentration and memory processing.
- Hard: High cognitive workload most difficult memory tasks in the virtual environment.

The gathered data set was used for training and testing the proposed deep learning models. The EEG signals were preprocessed and segmented into labelled samples and fed into the cognitive workload classification.

3.2 Experimental Setup

The experimental setup aimed to collect high quality EEG signals from participants who had to perform memory-based tasks while immersed in a virtual reality (VR) setup. The proposed system consists of a VR headset, an EEG acquisition system, gel-type electrodes, and a computer system that will record and store the EEG data in real-time.

During the data collection, the entire experimental setup was shown in Fig. 3.2. The OpenBCI Cyton board was connected to the laptop for EEG signal acquisition and monitoring, as shown in Figure 3.2.

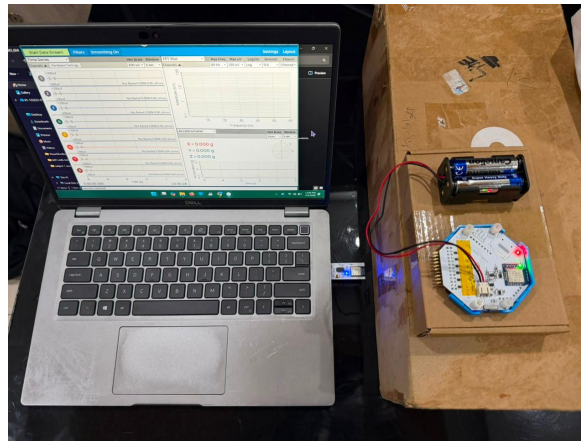


Fig. 3.2: OpenBCI Cyton board connected to the laptop

The recorded EEG signals were monitored through the graphical user interface (GUI), which provided a visual representation of the acquired EEG channels during the ex-

periment.

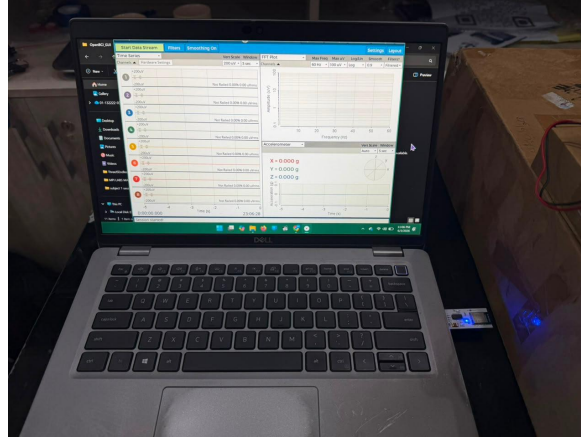


Fig. 3.3: Graphical user interface used for monitoring the acquired EEG signals.

During the experiment, participants performed the assigned VR tasks while wearing the Meta Quest 2 headset. EEG signals were recorded simultaneously during the VR-based cognitive tasks.

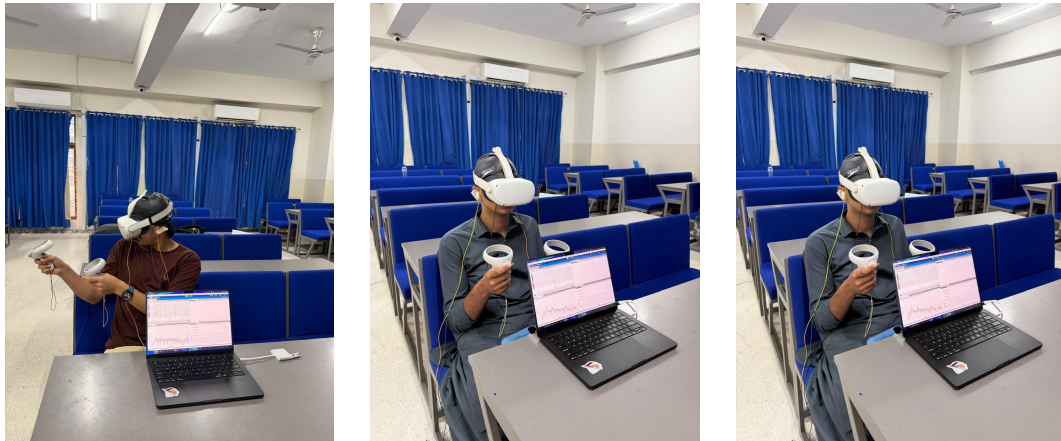


Fig. 3.4: Participants performing the VR-based cognitive workload assessment tasks.

The experimental setup aimed to acquire EEG data during cognitive tasks in a VR-situation. This experiment used a Meta Quest 2 VR headset and an OpenBCI Cyton 8-channel EEG acquisition board. The communication with the EEG acquisition system was established via a laptop computer, the recorded signals were monitored using the graphical user interface (GUI) and acquired signals were stored for further analysis. The electrodes were positioned on the participant's scalp prior to conducting the experiment based on the electrode placement configuration selected. The electrodes were wired to the Cyton board of OpenBCI and the quality of the signal was assessed using an acquisition interface. A single step was necessary to ensure that the EEG channels captured a steady EEG signal prior to the initiation of the VR task. The participant was then put on the Meta Quest 2 headset and engaged

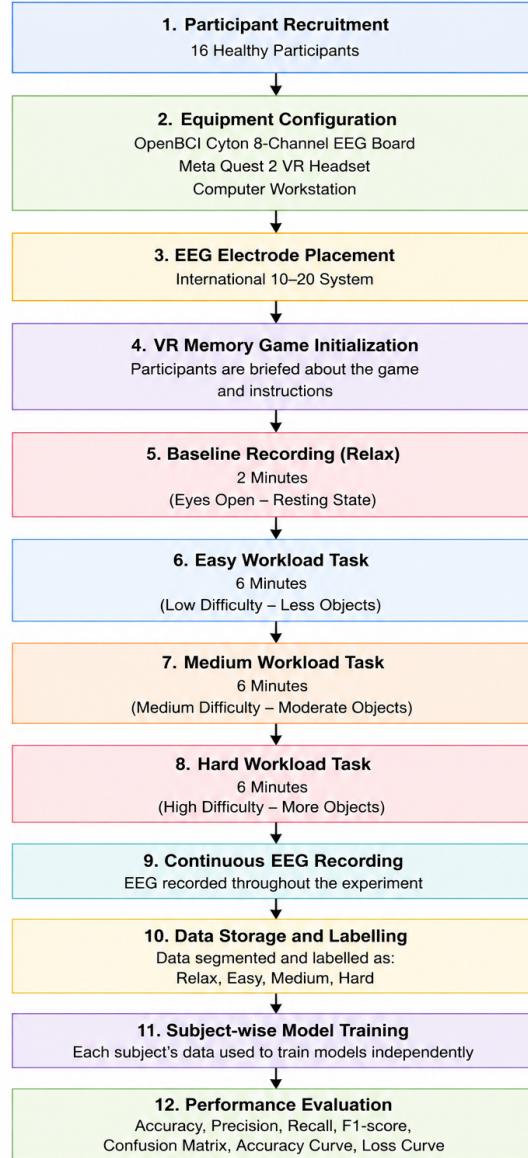


Fig. 3.5: Experimental Setup Of VR-EEG based System For Gamified Assessment

with the VR world. The tasks in the VR environment were created to have varying levels of cognitive complexity. The use of an immersive environment enabled the participants to carry out the tasks in a controlled and interesting environment while enabling the simultaneous acquisition of their EEG activity.

The experimental session comprised of a relaxation condition followed by three VR task conditions: Easy, Medium, and Hard. A baseline EEG recording was obtained under the relaxation condition, and each of the three VR conditions was a progressively more difficult and cognitively demanding task. The participant was tasked to work on the given task during each of the conditions, and the EEG signals were continuously recorded via the OpenBCI Cyton board. The acquired EEG data was sent to the laptop via the OpenBCI communication interface and displayed with the GUI software. The GUI gave a real-time display of the recorded EEG channels and thus

the acquisition process and signal quality to be monitored during the experiment. The recorded signals were then stored for pre-processing and cognitive workload modeling using the recorded signals. All participants underwent a constant experimental procedure in order to ensure similar recording conditions. The EEG data obtained was sorted by participant and task condition after the experimental sessions were finished. These recordings were then used to perform the following processing, feature preparation, model training and evaluation stages described below.

3.3 Hardware Components

The VR environment was designed to mimic a cognitive evaluation task that is gamified, where participants perform memory-related tasks of increasing difficulty. In the experiment, the participants interacted with the virtual environment through the Meta Quest 2 headset and their brain activity was recorded using the OpenBCI Cyton biosensing board. In order to assure stable signal acquisition, gel-based EEG electrodes were placed on the participant's scalp following the International 10–20 electrode placement system. The electrodes were attached to the OpenBCI Cyton 8-channel board which collected the EEG signals during the entire experiment. The signals recorded were relayed to the computer for real-time display, storage and later analysis. The procedure of the experiment included participant preparation, electrode placement, calibration of the EEG acquisition system, game playing with the VR system, and data recording. The impedance of each electrode was measured prior to the experiment to assure good signal quality. To reduce motion artifacts, participants were asked to be as relaxed as possible and to move as little as possible of their bodies and heads during the recording session. All of the system was built upon a high-performance computer that can perform simultaneous VR rendering and EEG signal acquisition. The EEG data collected from each recording session was stored for further preprocessing, feature extraction and training of the deep learning models. An EEG-based cognitive assessment system using virtual reality technology was proposed, and the hardware components used in the development of the proposed system were available on the market, which could acquire and correctly read the EEG signals and afford the immersive virtual reality environment. The experiment was set up using an OpenBCI Cyton 8-channel biosensing board, a Meta Quest 2 VR headset, gel-based EEG electrodes, and a computer system for data acquisition and processing.

3.3.1 OpenBCI Cyton 8-Channel Board

The OpenBCI Cyton is an open-source EEG acquisition board designed for neuroscience research and Brain-Computer Interface (BCI) applications. It is based on the Texas Instruments analog front-end (ADS1299), which offers high-resolution biopotential signal acquisition. The recording from eight EEG channels and sam-

pling frequency of 250 Hz allows the board to be used for simultaneous recording of fast brain responses for cognitive tasks. Throughout the experimentation, the Cyton board continuously captured EEG signals from all the connected electrodes and upload the captured data to the computer for storage and further analysis. It is portable, inexpensive, and works with open source software, making it suitable for cognitive workload assessment applications.

Table 3.1: Specifications of the OpenBCI Cyton Board [4]

Specification	Description
Device	OpenBCI Cyton Board
Microcontroller	PIC32MX250F128B
Analog Front End (AFE)	ADS1299 (24-bit ADC)
Number of EEG Channels	8 Channels (Expandable to 16 using Daisy Module)
Sampling Rate	250 Hz (Default)
ADC Resolution	24-bit
Voltage Resolution	0.298 μ V/bit
Input Voltage Range	± 2.5 V
Signal-to-Noise Ratio (SNR)	121 dB
Wireless Communication	RFduino Bluetooth Low Energy (BLE)
Storage	Micro SD Card Slot
Integrated Sensors	3-Axis LIS3DH Accelerometer
Power Supply	3–6 V DC Battery
Board Dimensions	2.41 $\times$ 2.41 inches
Software Interface	OpenBCI GUI / Python / MATLAB
Operating System Support	Windows, Linux, macOS

3.3.2 Meta Quest 2 Headset

The Meta Quest 2 is a standalone VR headset, which will be used to create an immersive gaming experience for players. It enables the user to interact with the virtual objects in natural way using the head tracking and handheld controllers without the need of external tracking sensors. For the cognitive assessment, the VR memory game was presented by the VR headset in this research. The virtual environment was highly immersive and able to capture participants attention and engagement throughout the experiment, allowing them to assess memory performance in natural and different workloads.

3.3.3 EEG Electrodes

High quality brain signals were gathered using reusable gel-based EEG electrodes. A conductive gel was placed between the scalp and the electrodes in order to reduce the electrode impedance and improve the quality of the signal. Electrodes were placed in the same position as per the International 10–20 electrode placement system, to ensure standardized EEG recording of all subjects. Each recording session was preceded by proper electrode placement and checking of the impedance to minimize the noise level and to ensure stable EEG recordings across the experiment.

3.3.4 EEG Electrode Placement

EEG data were collected with Cyton 8-channel Biosensing Board from OpenBCI. Electrodes were placed in the international 10–20 system which is a standardized and widely accepted system for acquisition of EEG signals. This standardisation of placement also allows for the consistent positioning of electrodes in all participants and increases the reliability and repeatability of brain signals recorded by the available brain signal recording system [2, 19]. The eight EEG electrodes were positioned over Fp1, Fp2, F3, F4, C3, C4, P3 and P4. The locations of the electrodes were chosen due to the fact that the frontal, central and parietal areas of the cerebral cortex are very important for cognitive functions like attention, working memory, executive control, sensory processing and decision making. Frontal electrodes (Fp1, Fp2, F3, and F4) mainly record neural activity related to attention, planning and executive function. The central electrodes (C3 and C4) are used to track sensorimotor processing and cognitive control, while the parietal electrodes (P3 and P4) track memory processing, spatial attention, and sensory integration [10, 13].

The scalp was treated with an alcohol swab prior to placement of the signal electrodes and conductive gel was placed over each electrode to minimize impedance and enhance signal quality. Before each recording session electrode connection was checked for stable and reliable signal acquisition. In the experiment, the subjects were asked to sit in a comfortable chair without unnecessary body movements and to blink their eyes and to relax their facial muscles to avoid motion artifacts and electromyographic (EMG) interference. Standardized electrode placement allowed high quality EEG signals to be recorded throughout the VR cognitive assessment experiment. The recorded signals were then used for pre-processing, feature extraction and cognitive workload classification with the suggested deep learning models.

3.4 EEG Signal Acquisition

The EEG signals utilized in this study were collected utilizing the open source Cyton 8-channel Biosensing Board, which is widely used in neuroscience research, brain–computer interface (BCI) applications and cognitive monitoring studies because of

its portability, flexibility and high quality signals [10, 19]. The board offers a stable solution for capturing multichannel EEG signals and facilitates real time EEG acquisition for experiments.

8 recording channels with a 24-bit analog-to-digital (ADC) resolution are provided on the OpenBCI Cyton board, which allows for high-precision recording of brain signals. EEG signals were sampled at 250 Hz in this research as the frequency is enough to take the common frequency components involved in cognitive activity. This is a sampling rate compatible with preserving the temporal characteristics of EEG signals and facilitating the accurate analysis of frequency bands commonly employed for cognitive workload assessments such as Theta (4-8 Hz), Alpha (8-13 Hz), and Beta (13-30 Hz) [10, 11].

All electrodes were firmly attached to the OpenBCI Cyton board and conductive gel was used to minimize electrode impedance and maximise signal quality before each recording session. All EEG channels were checked for quality prior to the experiment, to guarantee stable recordings and to reduce noise due to poor electrode contact or to external interference [19].

In the experimental part of the study, the experimental groups wore the EEG headset in conjunction with the Meta Quest 2 virtual reality headset, completing the memory tasks designed. Before the VR session, an EEG recording was performed to record the baseline brain activity and during the entire experiment. However, with continuous signal acquisition, it was possible to see how the neural activity changed as the participants played the VR memory game with various difficulty levels to examine the cognitive workload associated with different levels of task demands [5, 7].

Real-time recorded EEG signals were sent from the OpenBCI Cyton board to the acquisition computer where they were saved for later analysis. All these recordings were used as the main input of the next stage for preprocessing such as signal filtering, segmentation, feature extraction, and classification by the proposed deep learning classification models. EEG has the advantage of high temporal resolution, which allows for the detection of rapid neural responses during the game in relation to attention, working memory and cognitive processing [16, 17].

The Cyton board from OpenBCI board was advantageous for this research in the following ways. The lightweight and portable design enabled the participants to comfortably carry out the VR based tasks without limiting the free motion of the participants. Moreover, its compatibility with different software platforms and its ability to acquire high-quality EEG signals made it a suitable choice for developing the proposed VR-EEG system for gamified cognitive assessment [10, 19].

3.4.1 Virtual Reality Environment

The virtual reality (VR) environment was designed to create a virtual environment in which to assess participants' cognitive performance at varying levels of mental

workload. VR technology allows the development of a three-dimensional interactive environment that allows participants to interact with virtual objects in a natural way, in contrast to the traditional computer-based cognitive tests. This immersive experience makes users more engaged and gives a more realistic evaluation of the user's cognitive functions including attention, memory and decision making [5, 7].

This research developed the VR application with the Unity Game Engine that is widely used to create interactive virtual environments due to its flexibility, cross-platform compatibility, and real-time rendering capabilities. Unity offers a complete development environment, which allows integration with virtual reality hardware, interaction with created objects and physics-based simulations, and is therefore applicable in neuroscience and cognition assessment applications [6].

The virtual environment was experienced using the VR headset and handheld controllers of the Meta Quest 2, a standalone virtual reality system featuring inside out tracking system. The headset enables users to interact with virtual objects with freedom which would not otherwise be possible without the need for external tracking sensors, thus offering a comfortable and natural user experience. It features a high-resolution display and minimal latency, minimizing motion sickness and retaining the sense of immersion during the experimental session [23]. Each participant received a short introduction to this VR environment and was given ample time to get used to the headset and controllers before the experiment started. This familiarization session enabled participants to get an understanding on the interaction mechanism and minimized the learning effects during the real experiment. Once the orientation phase, participants were asked to execute the experimental tasks within the virtual environment with continuous EEG recording [7].

The virtual environment was specially created for memory assessment via a game-based approach. A traditional cognitive assessment was replaced by interactive memory-based activities presented in a fun virtual environment. Participants did not answer traditional cognitive tests, but rather completed interactive memory-based tasks in an interactive, fun environment. The game was designed at three difficulty levels: Easy, Medium and Hard, in order to elicit cognitive workload. Participants found the tasks progressively more difficult, requiring them to process increasingly more information, remember an increasing number of virtual objects, and make increasingly faster decisions as it proceeded. The use of virtual reality and EEG led to the simultaneous collection of behavioral and physiological data throughout the experiment. The task performance of the participants was recorded in the VR environment, and the EEG system simultaneously recorded neural activity related to attention, working memory, and cognitive workload. In this multimodal framework, gameplay behavior and real-time brain activity were integrated in a unified assessment of cognitive performance, which allowed for a more objective evaluation of cognitive performance [15, 16].

3.5 VR Memory Game Design

Also, an immersive VR environment proved to be better at keeping participants motivated and engaged than traditional screen-based cognitive assessments. The proposed system provided a more realistic testing environment with precise experimental control by presenting memory tasks in an interactive setting. The VR-EEG System for Gamified Assessment is based on the fusion of immersive technology with physiological monitoring. This proposed VR-EEG System for Gamified Assessment combines immersivity and physiological monitoring to better assess cognitive workload compared to current assessment methods.

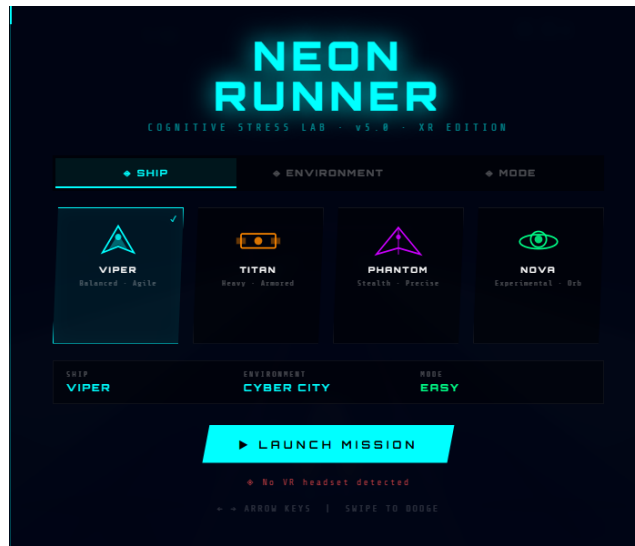


Fig. 3.6: Home page

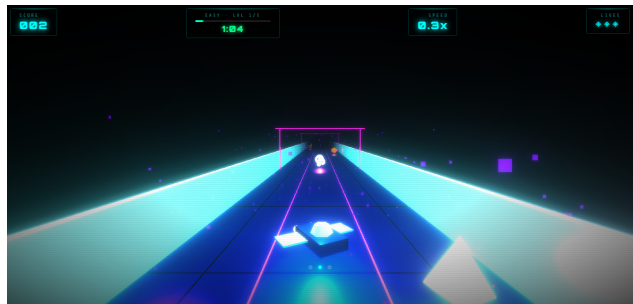


Fig. 3.7: Game 2

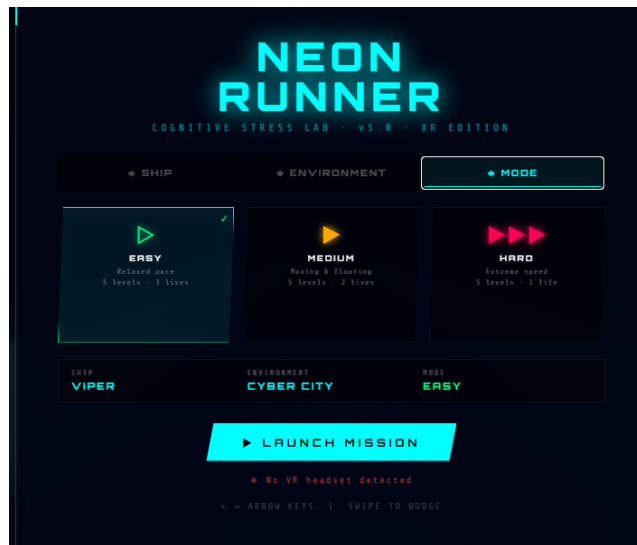


Fig. 3.8: Levels Of Game

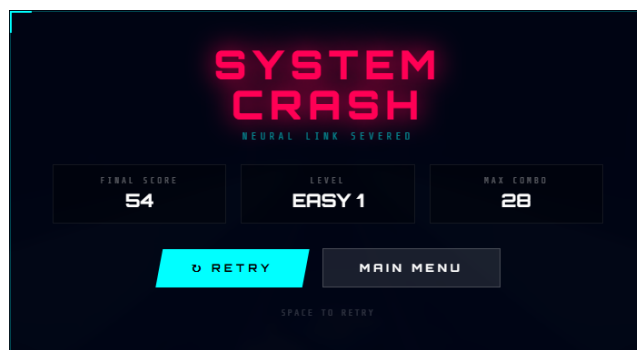


Fig. 3.9: Easy Level

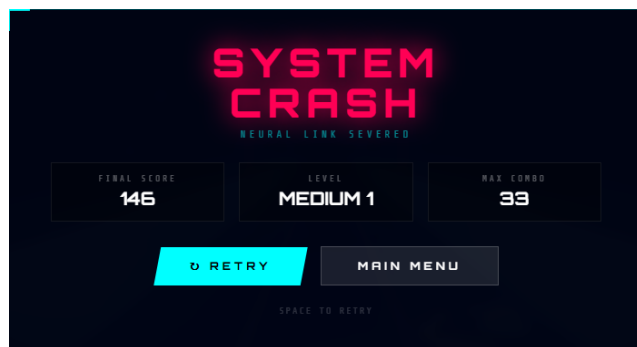


Fig. 3.10: Medium Level

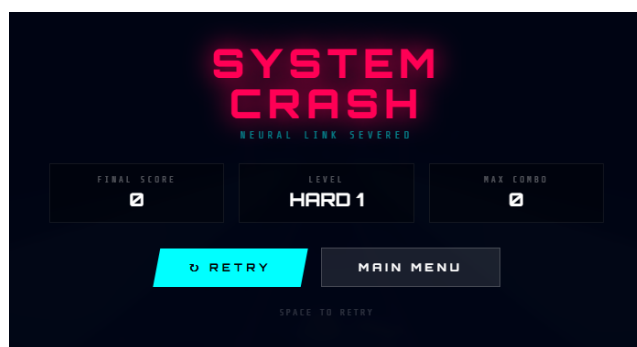


Fig. 3.11: Hard Level

The virtual reality memory game was designed as the main experimental memory task to measure participants' cognitive performance under varying mental workload. Rather than the usual memory tests, a gamified environment was created that generated an engaging and immersive experience while at the same time capturing the participants' brain activity via EEG. Gamification not only enhances the motivation of the users, but also helps users to actively participate in the experiment which leads to more natural behavioral responses when doing cognitive evaluation.

The game is played with the Meta Quest 2 virtual reality headset. Participants engaged with virtual objects via the headset's handheld controllers and were able to conduct memory-related tasks in a natural way in the 3D environment. The OpenBCI Cyton board continuously took EEG signals throughout the game to capture the neural responses for cognitive workloads [23]. The whole experiment was divided into four stages: Relaxation, Easy, Medium, and Hard. Each participant first underwent a relaxation exercise to set a baseline recording of the EEG. The participants during this period were calm and relaxed, equipped with the EEG headset and the VR headset. The baseline recording was used as a comparison to determine differences in brain activity for the following memory tasks. After the relaxation period, participants were asked to play three levels of the memory game, each more challenging than the last. The participants at each level were asked to watch, remember, and correctly identify virtual objects in the VR environment. The cognitive workload was increased by increasing the amount of information to be remembered, as well as the complexity of the task, across the difficulty modes of this game (Easy, Hard).

At **Easy level**, participants were made familiar with the game mechanics with a relatively low number of virtual objects. Participants had to learn to recognize and remember the objects presented and then match the correct ones from a list of several objects. Because the number of objects and the complexity of the decisions were constrained, this stage did not create too high an amount of cognitive load, and participants were able to get accustomed to the virtual environment. For the **Medium level**, the number of objects was increased, and the participants were required to hold more information in their memory prior to making their choices. Extra distractors were added to boost the memory interference and attention requirements. The participants consequently were required to possess more concentration and working memory to accomplish the task properly. The **Hard level** was the highest level of cognitive load. Participants had to learn more virtual objects in a short time frame while discriminating some distractors. This stage demanded higher cognitive workloads, which involved sustained attention, quicker decision making, and better working memory, and it was appropriate for high cognitive workload evaluation in this stage. EEG system continuously recorded brain activity throughout the entire experiment without interruption. The synchronization of the acquisition of gameplay events and EEG signals allowed for the direct comparison of participants'

behavior with their neural activities. By synchronizing these two, it was possible to analyze the influence of task difficulty on cognitive workload by means of objective physiological measures rather than only behavioural measures. The gamified design also had several practical benefits over traditional methods of cognitive assessment. VR technology kept participants engaged and provided an immersive experience that helped minimize the boredom often seen with repetitive memory tests. In addition, by using a virtual environment for providing the memory tasks, all participants were given the same experimental conditions and this increased the regularity and reliability of the collected data. Finally, the recorded EEG signals at Relaxation, Easy, Medium and Hard stages were the complete data set used in the upcoming stages for preprocessing, feature extraction and deep learning classification. The proposed VR-EEG system was tested on brain activity variations associated with varying cognitive workload and memory performance by using these recordings. These recordings allowed the VR-EEG system to explore brain activity changes at different cognitive workloads and memory performance levels.

3.6 Data Acquisition

The data acquisition process aimed at obtaining the electroencephalography (EEG) signals in a synced manner during the execution of memory-based tasks in the virtual reality (VR) environment. All of the participants used the OpenBCI Cyton EEG acquisition system and Meta Quest 2 VR headset at the same time in each experimental session. This set up allowed continuous recording of neural activity during the whole experiment without interference in the interaction with the virtual environment. The EEG headset was correctly placed on the participant's head following the international 10–20 system for electrode placement before the data recording started. The impedance of the electrodes was monitored to guarantee the quality of the signal and conductive gel was used as needed to achieve adequate contact between the scalp and electrodes. Careful positioning of the electrodes was crucial for ensuring that there was no signal distortion and reliable EEG recordings were achieved during the experiment. Eight EEG signals from Fp1, Fp2, F3, F4, C3, C4, P3, and P4, were continuously gathered by the OpenBCI Cyton board. The electrodes were chosen due to their front, central and parietal localization, which is strongly linked to attention, working memory, executive functions and cognitive workload. Brain activity changes across various stages of the memory task were sufficient to be analyzed, when recorded from multiple cortical regions, using an electroencephalogram (EEG) [2, 10].

All EEG signals were captured during the entire experimental session, including the relaxation stage and the 3 difficulty levels of the gameplay (Easy, Medium and Hard). With continuous recording there was no loss of important neural information during the transition between the task stages, and it was possible to compare brain

activity under different cognitive workload conditions. All participants performed the whole experiment in a single recording session, under the same experimental conditions. While collecting data, participants used the Meta Quest 2 handheld controllers to interact with the virtual objects in the environment with minimal unnecessary movement of the body. Considering the limited degree of head movement that is anticipated during typical VR interaction, any large head movements, eye blinking, jaw clamping and muscle activity were reduced by explicit experimental instructions. Removal of these artifacts improved the overall quality of the recorded EEG signals prior to further pre-processing as discussed in the following section [13].

All tests were conducted under the same experimental conditions, using the same procedure for the task, duration, environment and recording method for all participants. The tasks were then automatically presented by the VR application, and the brain signals were recorded during the presentation of the tasks and continuously stored in the EEG acquisition system for later analysis. The recordings were paired with task labels corresponding to the relaxation, easy, medium, and hard tasks; thereby allowing supervised learning in the training of the model. The acquired EEG recordings were the main physiological data utilized for this study. Once the signals were acquired, the recorded signals were exported for pre-processing, feature extraction and followed by classification using the proposed deep learning models. The synchronization of EEG acquisition during the entire VR memory game ensured that behavioral performance and neural responses could be analyzed simultaneously to objectively assess the cognitive workload in the VR memory game [9, 16].

3.7 Signal Preprocessing

The raw EEG signals obtained in the experimental sessions are not directly applicable for deep learning as they include various kinds of unwanted noise and artifacts. The imponderables are primarily caused by eye blinking, muscle movements, facial expressions, body movement, power line interference and poor electrode contact. The EEG signals do have very low amplitude so any disturbance of the signal of any magnitude can have a significant impact on the quality of the data recorded. Hence, a thorough preprocessing pipeline was created to enhance the quality of the speech signals prior to feature extraction and model training. The aim of the preprocessing was to retain the neural information that is important to the proposed cognitive workload classification models and eliminate any unnecessary parts that might affect the performance of models. The preprocessing step was performed in several sequential steps, such as checking the data, removing noise from the data, filtering the signal, reducing artifacts, segmenting data, processing the data into a final dataset suitable for deep learning. Figure 3.X depicts the entire preprocessing workflow used in this study. All EEG recordings from the OpenBCI Cyton board were first checked for

quality of recordings. The recordings were scanned to look for missing recordings, corrupted recordings or missing signal samples. The recordings had been carried out without any intermediary steps, and generated a dataset with very few missing values. Inconsistent data was removed for all other recordings that were incomplete or damaged to ensure consistency across the dataset. The EEG data was acquired from the eight electrodes (Fp1, Fp2, F3, F4, C3, C4, P3, and P4) with a sampling rate of 250 Hz. For this rate, the number of samples recorded for each channel are 250 per second. Even though the acquisition system uses high quality recordings, the raw EEG signals also include a slow baseline drift, environmental electrical interference, and high frequency noise. Those unwanted components need to be removed from the brain before the brains can be analyzed to obtain meaningful activity.

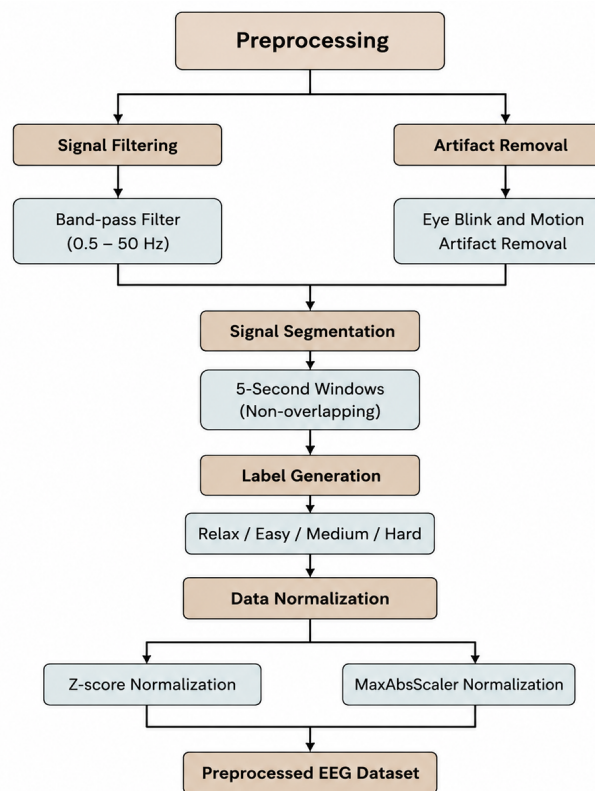


Fig. 3.12: Flowchart of EEG Data Preprocessing

A digital Butterworth band-pass filter was used to enhance the signal-to-noise ratio and attenuate low frequency drift and high frequency interference noise in each EEG channel. Because of the smoothness of its frequency response, the Butterworth filter was chosen for its characteristics because it would preserve the characteristics of the original waveform without introducing significant distortion to it. This pass-band, from 1 Hz to 40 Hz, was chosen because this frequency range contains the majority of the brain rhythms related to cognitive processing, and eliminates very slow baseline fluctuations and unwanted high frequency noise. Frequencies below 1 Hz are mostly baseline drift and frequencies above 40 Hz contain most of the muscle artifacts and environmental noise that are not relevant for mental workload analysis.

In addition to the frequency filtering, a notch filter at 50 Hz was implemented to reduce the power line interference which can be caused by electrical equipment in the laboratory environment. EEG signals are often contaminated by electrical interference, which can obscure signals of interest if not sufficiently filtered out. This interference was successfully reduced by notch filter without significantly interfering with adjacent EEG frequency bands.

Another important source of contamination in frontal EEG channels is eye blinking and eye movement. Electrooculographic (EOG) artifacts are a specific type of artifact that can be found in the frontal electrodes (Fp1 and Fp2) because they are near the eyes. The electromyographic (EMG) noise that could be picked up during the VR experiment can also be caused by jaw movement, facial muscle contraction, and head movement. To reduce the necessity of using complex artifact removal algorithms that could distort useful neural information, participants were asked to minimize excessive blinking, facial expressions, movement of the head and body during the game. These measures helped to minimize artifacts introduced by motions while keeping the interaction with the VR environment natural. The signals obtained after filtering were again checked visually to verify the success of the preprocessing stage in the quality of the obtained signals. Random signals from several participants were looked at to confirm that the characteristic EEG waveforms were not lost during filtering. This inspection also identified any abnormal recordings which may have still been containing excessive noise.

After cleaning the signals, they were segmented into smaller analysis windows via a segmentation process. By partitioning continuous EEG data into smaller bouts, deep learning models can better capture the temporal aspects of brain activity and have a greater number of training examples. The 24 continuous EEG recordings of each subject were segmented into the cognitive workload conditions of their game activity in this study. Four cognitive states (Relaxation, Easy, Medium and Hard) were recorded at each recording session. The workload label was inherited by the segmented windows according to the experimental stage in which they were recorded. The Relaxation recordings were the baseline cognitive state when participants were not playing the VR memory game but were calm. The Easy stage was associated with low level of cognitive load, the Medium stage was associated with moderate level of cognitive load, by increasing the memory task complexity. The Hard stage had the most demanding mental demand as it asked participants to remember more virtual objects and make quick decisions with high cognitive load. As a consequence, a labeling strategy was set up, allowing supervised learning when training the model, because each EEG segment had a predetermined workload class.

After segmentation, a normalization was done to minimize amplitude differences from participant to participant. Without proper management, deep learning models can learn the characteristics of individual participants instead of cognitive workload patterns. Thus, normalization was performed on every EEG channel to make sure

that all the channels have equal contribution to learning the features. The signals were then reordered into a structured form, appropriate for deep learning architectures. Each EEG segment included synchronised signals from each of the eight channels of recording, maintaining the temporal information and spatial relationships between the various brain regions. The data was sorted so that each sample has multichannel EEG data and its corresponding workload label. Finally, the processed EEG data were exported for feature extraction and deep learning analysis. After pre-processing, each EEG recording was subject to filtering and artifact reduction, segmentation, normalization and labelling. The resulting dataset enabled the proposed deep learning architectures to learn discriminative features related to various levels of cognitive workloads in a clean and standardized representation of brain activity.

3.8 Proposed Deep Learning Models

The proposed VR-EEG system involves using deep learning methods to automatically identify various levels of cognitive workload by analyzing preprocessed EEG data. The ability to learn meaningful spatial and temporal representations directly from brain signals automatically with deep learning makes it one of the most effective methods for EEG analysis. Deep neural networks can extract nonlinear relationships between the various features present in EEG data, which are more complex than those that can be extracted by traditional machine learning techniques, and thus provide better classification accuracy for cognitive workload assessment [17, 20].

In this research, three different deep learning architectures were implemented and evaluated. The first architecture is called Multi-Branch Attentive EEGNet (MBA-EEGNet), which is an extension of the original EEGNet with multiple parallel convolutional branches to enhance the extraction of features from EEG signals. The second architecture is Multi-Scale Dynamic Graph Cross-Attention Conformer (MS-DGCA Conformer), a hybrid of graph learning and transformer-based attention mechanisms, that models both spatial and temporal relationships between EEG channels. To enhance the performance of feature learning and cognitive workload classification, a hybrid architecture of MS-DGCA-MBA-EEGNet was proposed which combines the merits of both networks.

In the pre-processing and feature extraction stage, the feature representations of EEG signals are normalized and fed to the proposed models. All eight EEG channels (Fp1, Fp2, F3, F4, C3, C4, P3 and P4) have extracted Theta, Alpha, Beta and Relative Band Power features and are passed into the deep learning networks. In the training phase, each EEG segment is correlated with one of 4 workload classes: Relaxation, Easy, Medium, Hard, and the networks learn discriminative representations for each of the different cognitive demands.

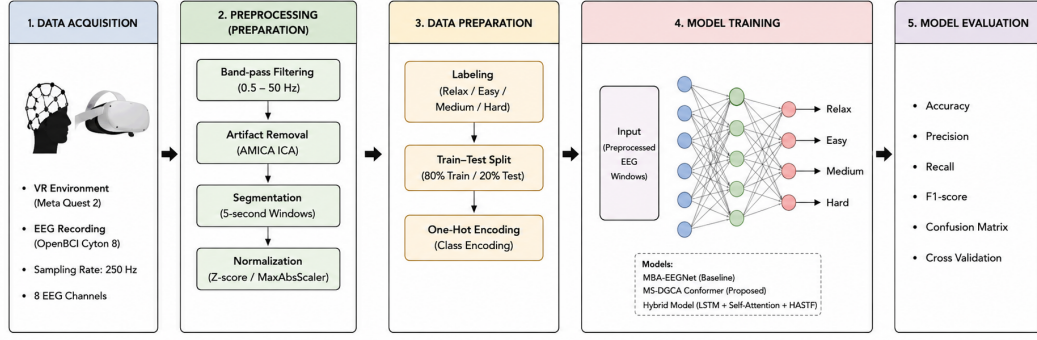


Fig. 3.13: Overall Deep Learning Framework

3.8.1 Multi-Branch Attentive EEGNet (MBA-EEGNet)

MBA-EEGNet is the first deep learning architecture that is applied in this research. The proposed model is based on EEGNet proposed by Lawhern et al. [17] for EEG based brain computer interface (BCI) applications. EEGNet has attracted a lot of interest due to its high classification accuracy with a significantly reduced number of trainable parameters compared to traditional CNN networks. This lightweight architecture is appropriate for EEG analysis as datasets can be small.

Original EEGNet works well on many of the EEG classification problems, but it is a single processing pathway. The cognitive workload assessment signals recorded from the EEG contain complex temporal and spatial information distributed across different brain regions. One feature extraction branch, therefore, might not necessarily be able to capture all the important neural properties corresponding to varying levels of mental workload. In order to address this limitation, the proposed research utilizes the Multi-Branch Attentive EEGNet (MBA-EEGNet) that incorporates multiple parallel convolutional branches along with an attention mechanism.

MBA-EEGNet is divided into three major steps: temporal feature extraction, spatial feature extraction and attention based feature fusion. The normalized EEG feature matrix obtained in the pre-processing stage is fed into the network as its initial input. The input is sent through several convolution branches, rather than only one convolution pathway. In each branch, a different size convolution kernel is used to learn complementary information from the EEG signals at various receptive fields. Small kernels are more useful for detecting fine time variations while big kernels are more useful for extracting broad contextual information from long EEG segments.

The first operation carried out by the network is temporal convolution which is used to detect frequency related patterns from the EEG recordings. The temporal convolution operation can be written for an input EEG signal X as

$$Y_i = X * W_i + b_i \quad (3.1)$$

where,

X represents the input EEG signal. $Conv_{1D}$ denotes the one-dimensional convolution operation. F_t represents the extracted temporal feature map.

After temporal convolution, the network conducts depthwise convolution to learn the spatial relationships between different EEG channels. In contrast to traditional convolution, depthwise convolution computes the convolution of each feature map separately, resulting in faster computation, while maintaining the discriminative spatial information. This operation allows the model to learn about correlations between various electrode positions (e.g., Fp1, Fp2, F3, F4, C3, C4, P3, and P4) that are tightly linked to attention, executive control and working memory functions [20].

$$Z = Y \otimes W_d \quad (3.2)$$

where Y denotes the input feature map obtained from the previous layer, W_d represents the depthwise convolution kernel applied independently to each input channel, $\otimes$ denotes the depthwise convolution operation, and Z denotes the output feature map generated after the depthwise convolution.

Depthwise convolution independently processes each EEG channel, allowing the model to learn spatial relationships among electrodes while significantly reducing the number of trainable parameters. A number of convolution branches are used in parallel to enhance the diversity of features. Every branch takes in a different representation of EEG signal with different kernels of receptive field. Finally, the extracted feature maps are combined together to create a more complete representation, which is then fed into the attention module. If the output feature maps of the parallel branches are denoted by F

$$F_{\text{concat}} = \text{Concat}(F_1, F_2, \dots, F_n) \quad (3.3)$$

where $F_1, F_2, \dots, F_n$ represent the feature maps extracted from the parallel convolution branches of the MBA-EEGNet architecture. The $\text{Concat}(\cdot)$ operation concatenates these feature maps along the channel dimension to form a unified feature representation, denoted by F_{concat} . This combined feature map preserves complementary spatial and temporal information learned by different branches, enabling the network to capture multi-scale EEG patterns associated with varying cognitive workload levels. Following feature fusion, an attention mechanism is used to focus more on informative features and reduce redundant or less useful information. The attention module has adaptive weights learned during the training of the network, and automatically focuses on features that are more significant in the classification of workloads.

The weights of attention are calculated by Softmax function.

$$\alpha_i = \frac{e^{s_i}}{\sum_{j=1}^n e^{s_j}} \quad (3.4)$$

where α_i represents the normalized attention weight assigned to the i^{th} feature. The value s_i denotes the attention score computed for that feature, while n is the total number of extracted features. The Softmax function normalizes all attention scores so that their weights sum to one, allowing the model to emphasize the most informative features while suppressing less relevant ones. Then the weighted feature representation is obtained as:

$$F_{\text{att}} = \sum_{i=1}^n \alpha_i F_i \quad (3.5)$$

where F_{att} is the attention-weighted feature map, α_i denotes the attention weight of the i^{th} feature map, F_i represents the extracted feature map, and n is the total number of feature maps. Finally, a fully connected layer and a Softmax layer are used to determine one of the 4 workload classes, using the attended feature representation. The output logits are converted to probabilities through the use of the Softmax function which does the following:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^C e^{z_j}} \quad (3.6)$$

Equation 3.6 represents the Softmax activation function used in the output layer of the proposed MBA-EEGNet model. It converts the output logits into probability values for each cognitive workload class. Here, z_i denotes the output score of class i , C represents the total number of classes, and $P(y_i)$ is the predicted probability that the input EEG sample belongs to class i . The class with the highest probability is selected as the final prediction. There are several benefits of the use of the MBA-EEGNet architecture for cognitive workload classification. To achieve this, multiple branches of the convolution are used, which allows the extraction of both local characteristics of the EEG and global characteristics. Second, the task of selecting the most informative features is automatically performed by the attention mechanism, which leads to a more discriminative ability while not adding much computational complexity. Lastly, due to the inherent low computational cost of EEGNet, the extended MBA-EEGNet has a relative low computational cost while representing more features for the EEG-based cognitive workload assessment.

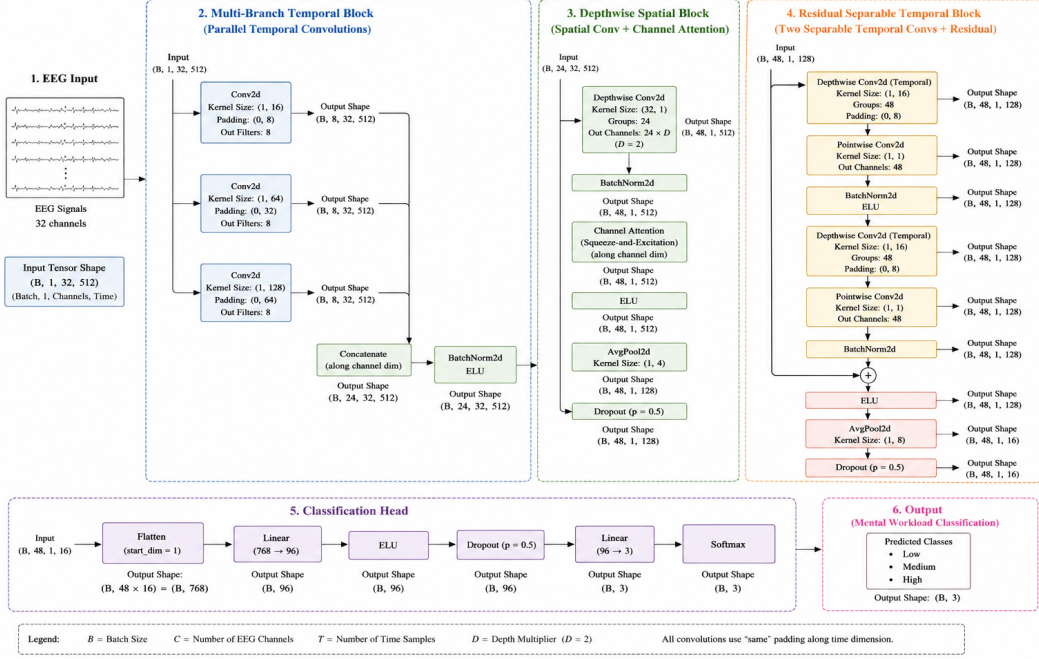


Fig. 3.14: Architecture of the Proposed Multi-Branch Attentive EEGNet (MBA-EEGNet)

3.8.2 MS-DGCA Conformer

In this research, the second deep learning architecture is proposed: Multi-Scale Dynamic Graph Cross-Attention Conformer (MS-DGCA Conformer). The motivation behind the proposed model is to learn temporal and spatial features of EEG signals for cognitive workload classification. The proposed architecture is able to model the functional relationships among the different EEG channels as well as mostly local temporal information captured by conventional convolutional neural networks. Learning the channel dependencies allows the model to generate a more discriminative representation of cognitive workload because the activity of a specific brain region is generated through interactions of multiple brain regions.

The preprocessed EEG signals are fed to several one-dimensional convolutional branches initially. Convolution branches use different kernels to allow the capturing of EEG patterns on different temporal resolution. Short duration neural fluctuations are learned by small convolution kernels, while long duration, temporal dependencies are learned by larger convolution kernels which reflect sustained attention and working memory. The advantage of multiple receptive fields is that the network can maintain more temporal information than would a single-scale convolutional architecture.

The convolution operation can be expressed as

$$F_i = \sigma(X * W_i + b_i) \quad (3.7)$$

The formula is: where X is the input EEG signal, W_i is the convolution kernel of the i^{th} branch, b_i is the bias term of the i^{th} branch, $\sigma(\cdot)$ is the activation function, and F_i is the extracted feature map of the i^{th} branch.

All the convolution branches output feature maps which are fused to form a holistic representation of the EEG signal.

$$F_{multi} = \text{Concat}(F_1, F_2, \dots, F_n) \quad (3.8)$$

The feature maps $(F_1, F_2, \dots, F_n)$ learned from various kernel sizes are combined to form the multi-scale feature representation (F_{multi}) .

The multi-scale representation allows information from different temporal scales to be preserved in the proposed model. Thus, neural oscillations and slowly varying EEG characteristics both have a role in classification of cognitive workload.

The EEG channels are mapped to graph nodes after the temporal features are extracted. Unlike traditional architectures, the proposed architecture dynamically discovers functional relationships between different brain regions without assuming any constant connectivity between them. This adaptive graph representation can be used to model the changing neural interaction during the various cognitive workload conditions.

Adjacency matrix of the dynamic graph is calculated as

$$A = \text{Softmax} \left(\frac{QQ^T}{\sqrt{d}} \right) \quad (3.9)$$

Here, Q is the representation of the learned node, d is the dimension of features and A is the dynamically computed adjacency matrix that captures the relationship among EEG channels.

The dynamic graph enables the network to automatically discover meaningful channel interactions instead of relying on predefined electrode connectivity.

Once the construction of the graph, a graph cross-attention mechanism is used to select the most informative EEG channels. It gives more weight to the more crucial parts of the brain and less to less informative channels.

The attention weights are calculated as

$$\alpha = \text{Softmax} \left(\frac{QK^T}{\sqrt{d}} \right) \quad (3.10)$$

In this case, the query matrix Q and the key matrix K are respectively defined as the query and the key matrices, and the attention coefficients assigned to each EEG channel are represented by the matrix α .

The refined graph representation is then given by

$$F_{graph} = \alpha V \quad (3.11)$$

where V is the value matrix and F_{graph} is the attention enhanced graph features.

The attention mechanism allows the network to selectively attend to highly discriminative cortical regions involved in attention, executive function and working memory, while inhibiting redundant neural activity.

The enhanced graph features are then passed on to the Conformer encoder. The Conformer also incorporates the Transformer's self-attention mechanism to capture long-range contextual dependencies while also using convolutional layers to represent local temporal information, thus enabling the model to learn both dependencies at the same time.

A multi-head self-attention mechanism is defined as

$$\text{Attention}(Q, K, V) = \text{Softmax} \left(\frac{QK^T}{\sqrt{d}} \right) V \quad (3.12)$$

In which Q represents query matrix, K represents key matrix, and V represents value matrix.

Multi-heads with multiple attention heads are computed to capture various contextual relationships among EEG features.

$$\text{MHA} = \text{Concat}(\text{head}_1, \dots, \text{head}_h)W \quad (3.13)$$

where W is the learnable projection matrix, and head_i is the output of the i^{th} attention head.

A feed-forward network further fine-tunes the learned representation after the attention module.

$$\text{FFN}(x) = W_2(\text{ReLU}(W_1x + b_1)) + b_2 \quad (3.14)$$

The parameters W_1 , W_2 , b_1 and b_2 in this case are the learnable parameters of the feed-forward network.

Lastly, the feature vector extracted is passed to the output layer where the cognitive workload is predicted. The network outputs are transformed to probability values for each workload class by the Softmax classifier.

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^C e^{z_j}} \quad (3.15)$$

The output score of class i is z_i and the number of workload classes is C and $P(y_i)$ is the probability that the EEG sample is assigned to class i .

The category that has the greatest chance of occurring is the final prediction. The proposed MS-DGCA Conformer successfully models the spatial and temporal characteristics of the EEG signal via the multi-scale temporal learning, adaptive graph modelling, graph cross-attention and Conformer encoding. This complete feature representation allows for better separation of Relaxation, Easy, Medium and Hard cognitive workload states in the context of VR memory assessment.

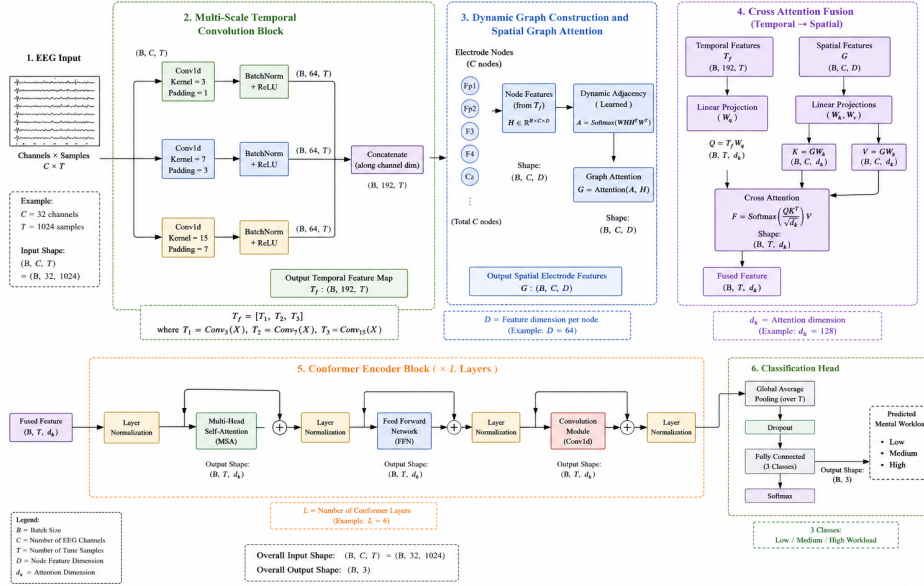


Fig. 3.15: Architecture of the MS-DGCA Conformer

3.8.3 MS-DGCA-MBA-EEGNet Hybrid Architecture

The limitations of using a single deep learning architecture for EEG-based cognitive workload classification motivated the development of a hybrid model in this study. The proposed hybrid architecture, named the Multi-Scale Dynamic Graph Cross-Attention Multi-Branch EEGNet (MS-DGCA-MBA-EEGNet), integrates the complementary characteristics of the Multi-Branch Attentive EEGNet (MBA-EEGNet) and the Multi-Scale Dynamic Graph Cross-Attention Conformer (MS-DGCA Conformer).

The main objective of the hybrid architecture is to obtain a richer representation of EEG activity by jointly learning short-term temporal patterns, multi-scale temporal characteristics, spatial relationships between EEG channels, dynamic feature dependencies, and long-range contextual information. The MBA-EEGNet component contributes efficient convolution-based feature extraction and channel attention, whereas the MS-DGCA component introduces dynamic graph-based learning, cross-attention, and Conformer-based contextual modeling.

The complete hybrid network is organized into six main processing stages:

1. Multi-Branch Temporal Convolution,
2. Depthwise Spatial Convolution with Channel Attention,
3. Dynamic Graph Attention,
4. Cross-Attention Fusion,
5. Residual Separable Temporal Processing, and
6. Conformer Encoding.

The representation generated by these stages is subsequently aggregated using global average pooling and passed to a classification head for prediction of the cognitive workload class.

The input to the proposed network is represented as an EEG tensor with dimensions $B \times C \times T$, where B denotes the batch size, C represents the number of EEG channels, and T represents the number of temporal samples. Since eight EEG channels were acquired using the OpenBCI Cyton board, the input representation used in the proposed system is defined as:

$$X \in \mathbb{R}^{B \times 8 \times 512} \quad (3.16)$$

where eight corresponds to the EEG channels Fp1, Fp2, F3, F4, C3, C4, P3, and P4, while 512 represents the number of temporal samples in an input segment.

The input tensor is appropriately reshaped before applying the two-dimensional convolutional operations used in the initial feature extraction stage.

3.8.3.1 Multi-Branch Temporal Convolution

The first processing stage of the hybrid architecture performs multi-scale temporal feature extraction. Instead of depending on a single temporal convolution, three parallel convolutional branches are employed. Each branch uses a different kernel length so that EEG characteristics occurring over different temporal intervals can be learned simultaneously.

The three branches use kernel sizes of 1×16 , 1×64 , and 1×128 , respectively. Each branch produces eight feature maps. Consequently, the outputs of the three branches provide a combined representation containing 24 feature maps.

For the i^{th} branch, the temporal convolution can be expressed as:

$$F_i = \sigma(X * W_i + b_i) \quad (3.17)$$

where X represents the input EEG tensor, W_i is the convolution kernel associated

with the i^{th} branch, b_i is its corresponding bias, $\sigma(\cdot)$ represents the activation function, and F_i denotes the feature representation generated by that branch.

The outputs from the three branches are concatenated along the feature dimension:

$$F_{\text{total}} = \text{Concat}(F_1, F_2, F_3) \quad (3.18)$$

Since each branch produces eight feature maps, the resulting representation contains:

$$F_{\text{total}} = 8 + 8 + 8 = 24 \quad (3.19)$$

feature maps.

The use of different temporal kernel sizes enables the network to analyze EEG activity at multiple temporal resolutions. The smaller kernel is capable of responding to localized temporal variations, whereas the larger kernels provide a broader temporal context. This combination is useful for cognitive workload analysis because EEG patterns associated with mental processing may occur over different time scales.

Following concatenation, batch normalization is applied to stabilize the feature distributions during training. The normalized representation is then passed through an ELU activation function to introduce nonlinear transformations and improve the learning capability of the network.

3.8.3.2 Depthwise Spatial Convolution and Channel Attention

The second stage focuses on extracting spatial information from the multi-scale temporal representation. A depthwise convolution is employed to learn spatial filters across the EEG channel dimension while maintaining a relatively low computational cost.

The spatial filtering operation is represented by:

$$F_{\text{spatial}} = F_{\text{total}} \otimes W_d \quad (3.20)$$

where F_{total} denotes the feature representation obtained from the temporal convolution stage, W_d represents the depthwise convolution kernel, $\otimes$ denotes the depthwise convolution operation, and F_{spatial} represents the resulting spatial feature representation.

The temporal feature representation contains 24 feature maps and a depth multiplier of 2 is employed in the depthwise convolution. Therefore, the spatial convolution produces 48 feature maps.

Depthwise convolution allows each feature map to be spatially processed without performing a full convolution across all feature maps. As a result, the number of

trainable parameters is considerably lower than that of a conventional convolution while still allowing the network to learn spatial relationships between EEG representations.

Batch normalization is subsequently applied to the spatial representation. The resulting features are then supplied to a channel attention module based on the Squeeze-and-Excitation mechanism. The purpose of this module is to adaptively determine which feature channels contribute most strongly to cognitive workload classification.

The squeeze operation summarizes each feature channel by calculating its average activation over the temporal dimension:

$$s_c = \frac{1}{T} \sum_{t=1}^T F_{c,t} \quad (3.21)$$

where $F_{c,t}$ denotes the activation of channel c at temporal position t , T is the temporal dimension, and s_c represents the summarized descriptor of channel c .

The resulting channel descriptor is passed through two fully connected transformations. The first transformation reduces the dimensionality from 48 to 6 and is followed by a ReLU activation. The second transformation restores the dimensionality from 6 to 48 and applies a Sigmoid activation to generate channel-wise attention coefficients:

$$a = \sigma(W_2 \text{ReLU}(W_1 s + b_1) + b_2) \quad (3.22)$$

where s denotes the squeezed channel descriptor, W_1 and W_2 are trainable weight matrices, b_1 and b_2 are bias vectors, and $\sigma(\cdot)$ denotes the Sigmoid activation function.

The generated attention coefficients are applied to the spatial feature representation using element-wise multiplication:

$$F_{\text{att}} = a \odot F_{\text{spatial}} \quad (3.23)$$

where a represents the learned channel attention weights, $\odot$ denotes element-wise multiplication, and F_{att} is the resulting channel-refined representation.

This mechanism enables the network to increase the contribution of informative feature channels while suppressing representations that provide limited information for workload discrimination.

An ELU activation is applied after channel attention, followed by average pooling with a pool size of 1×4 . A dropout rate of 0.5 is then employed to reduce overfitting. The resulting feature representation can be expressed as:

$$F_{\text{pool}} \in \mathbb{R}^{B \times 48 \times 1 \times T'} \quad (3.24)$$

where T' denotes the reduced temporal dimension. For the specified pooling operation:

$$T' = \frac{T}{4} \quad (3.25)$$

3.8.3.3 Dynamic Graph Attention

The third stage introduces dynamic graph learning to model relationships within the extracted EEG representations. Rather than defining the connectivity between EEG features manually, the proposed module learns these relationships directly from the input representation.

The pooled representation is first transformed into a sequential form:

$$H = \text{Reshape}(F_{\text{pool}}) \in \mathbb{R}^{B \times T' \times 48} \quad (3.26)$$

Thus, each temporal position is represented by a 48-dimensional feature vector.

Three trainable linear transformations are used to obtain the query, key, and value representations:

$$Q = HW_Q \quad (3.27)$$

$$K = HW_K \quad (3.28)$$

$$V = HW_V \quad (3.29)$$

where W_Q , W_K , and W_V are learnable projection matrices.

The relationships between the feature representations are determined using scaled dot-product attention. The resulting matrix is used as a dynamic adjacency representation:

$$A = \text{Softmax} \left(\frac{QK^T}{\sqrt{d}} \right) \quad (3.30)$$

where d denotes the dimensionality of the projected feature space. The matrix A describes the dynamically learned relationships between the feature representations.

The graph-enhanced representation is then calculated as:

$$G = AV \quad (3.31)$$

where G represents the graph-aware feature representation.

The dynamic graph mechanism allows the network to learn data-dependent relationships instead of depending on a fixed connectivity pattern. This is particularly useful for EEG analysis because the interaction between brain regions may vary according to the participant and the cognitive workload condition.

3.8.3.4 Cross-Attention Fusion

The fourth stage combines the temporal information obtained from the MBA-EEGNet component with the graph-based representation produced by the dynamic graph module. Cross-attention is used to allow one representation to selectively retrieve relevant information from the other representation.

The temporal representation is first projected into a query space, while the graph representation is transformed into key and value spaces:

$$Q_T = F_T W_Q \quad (3.32)$$

$$K_G = G W_K \quad (3.33)$$

$$V_G = G W_V \quad (3.34)$$

where F_T represents the temporal feature representation, G denotes the graph-based representation, and W_Q , W_K , and W_V are learnable projection matrices.

The cross-attention operation is defined as:

$$F_{\text{cross}} = \text{Softmax} \left(\frac{Q_T K_G^T}{\sqrt{d}} \right) V_G \quad (3.35)$$

This operation enables temporal EEG features to selectively attend to relevant graph-based spatial representations. Consequently, the network can determine which spatial relationships are most relevant to the temporal patterns being analyzed.

To preserve the original temporal information, a residual connection is introduced:

$$F_{\text{fusion}} = F_{\text{cross}} + F_T \quad (3.36)$$

The residual connection preserves the original temporal representation while incorporating the information obtained through cross-attention. It also supports more

stable gradient propagation during network optimization.

3.8.3.5 Residual Separable Temporal Block

The fifth stage performs additional temporal refinement using a residual separable convolutional block. This component is derived from the lightweight convolutional design principles used in EEGNet and is intended to enhance temporal feature learning without introducing a large computational burden.

The block uses depthwise separable convolution, where each separable convolution consists of a depthwise temporal convolution followed by a pointwise 1×1 convolution.

The first depthwise convolution is expressed as:

$$F_{dw1} = F_{\text{fusion}} * W_{dw1} \quad (3.37)$$

where W_{dw1} represents the depthwise temporal convolution kernel with a temporal size of 16×1 .

A pointwise convolution is then applied:

$$F_{pw1} = F_{dw1} * W_{pw1} \quad (3.38)$$

where W_{pw1} denotes the pointwise convolution kernel.

The resulting representation is normalized using batch normalization and passed through an ELU activation function. A second depthwise separable convolution is then applied using the same temporal kernel dimension.

A residual connection combines the processed representation with the original input:

$$F_{\text{res}} = F_{\text{sep}} + F_{\text{fusion}} \quad (3.39)$$

where F_{sep} denotes the output of the stacked separable convolution operations and F_{res} represents the final output of the residual block.

The residual pathway helps preserve useful information and facilitates gradient propagation through the network. Following the residual processing, average pooling with a pool size of 8 is applied to reduce the temporal dimension. A dropout rate of 0.5 is subsequently used to improve generalization and reduce the risk of overfitting.

3.8.3.6 Conformer Encoder

The final feature learning stage consists of a Conformer encoder. The Conformer combines self-attention with convolution-based processing and feed-forward trans-

formations. This combination enables the network to capture both long-range dependencies and local temporal characteristics within the EEG representation.

The proposed hybrid architecture contains four Conformer encoder layers. Each layer uses a feature dimension of 48 and eight attention heads.

The self-attention mechanism is defined as:

$$\text{Attention}(Q, K, V) = \text{Softmax} \left(\frac{QK^T}{\sqrt{d}} \right) V \quad (3.40)$$

where Q , K , and V represent the query, key, and value matrices, respectively, and d denotes the dimensionality of an attention head.

Multiple attention heads are computed in parallel to allow the model to learn different relationships within the EEG feature sequence. Their outputs are concatenated and projected using a learnable output matrix:

$$\text{MHA} = \text{Concat}(\text{head}_1, \dots, \text{head}_h)W_O \quad (3.41)$$

where $h = 8$ represents the number of attention heads and W_O denotes the learnable output projection matrix.

In addition to self-attention, the Conformer encoder contains a convolutional module based on depthwise convolution. This component captures local temporal relationships that may not be adequately represented by global self-attention alone. Therefore, the convolutional and attention mechanisms operate together to provide both local and global contextual information.

The feed-forward component of the Conformer is represented by:

$$\text{FFN}(x) = W_2 \text{GELU}(W_1 x + b_1) + b_2 \quad (3.42)$$

where W_1 and W_2 are learnable weight matrices, b_1 and b_2 are bias vectors, and $\text{GELU}(\cdot)$ represents the Gaussian Error Linear Unit activation function.

The combination of multi-head self-attention, convolutional processing, and feed-forward transformation enables the Conformer encoder to construct a contextual representation of the EEG sequence. This representation incorporates information from both short-range temporal patterns and long-range dependencies that may be associated with different cognitive workload conditions. After the Conformer encoder, the learned feature representation is passed through a global average pooling operation. The pooled representation is then supplied to the final classification head. The classification layer produces a probability distribution over the four workload categories: Relaxation, Easy, Medium, and Hard. The final prediction is obtained by selecting the class with the highest predicted probability. Therefore, the com-

plete MS-DGCA-MBA-EEGNet architecture combines multi-scale temporal feature extraction, spatial feature learning, channel attention, dynamic graph modeling, cross-attention fusion, residual temporal processing, and Conformer-based contextual learning within a single framework. This integrated design enables the proposed system to learn complementary EEG characteristics and provides a comprehensive representation for automatic cognitive workload classification in the VR-based memory assessment environment.

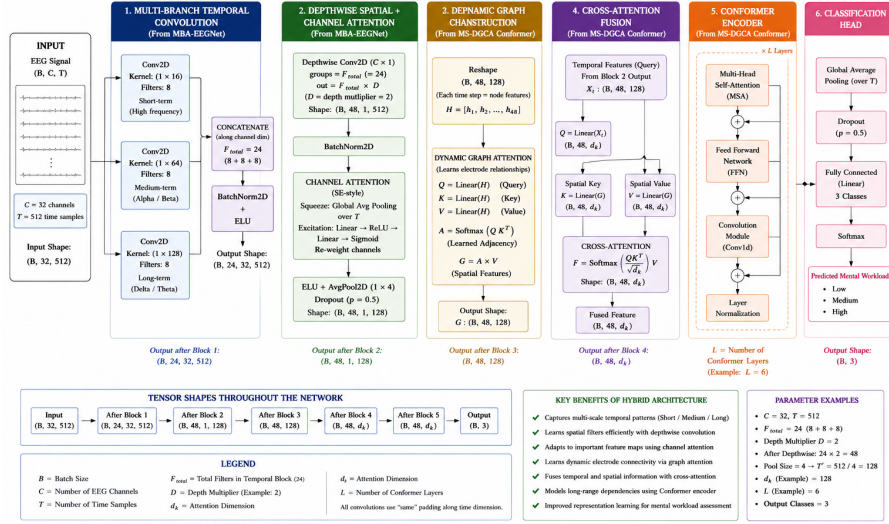


Fig. 3.16: Architecture of Hybrid Model.

Chapter 4

Implementation

This chapter introduces the proposed VR-EEG Cognitive Workload Classification System and its implementation and testing. The proposed framework combines a virtual reality (VR) based memory game, electroencephalography (EEG) signal acquisition and deep learning to automatically categorize various cognitive workload levels. The overall process of implementing the flow is described in this chapter, along with the software development environment, the system architecture, and the implementation of the model and the tests that were followed during the study. This implementation was made implementing the recorded EEG signals obtained from the OpenBCI Cyton board to process, analyze and classify their signals into different cognitive workload levels with the support of Python based deep learning frameworks. The full pipeline of implementation involves loading the EEG data, pre-processing, extracting features, applying the proposed deep learning architectures, training the model, testing the model, and performing the evaluation. In this work, three deep learning architectures were implemented and compared: The proposed Multi-Branch Attentive EEGNet (MBA-EEGNet), the Multi-Scale Dynamic Graph Cross-Attention Conformer (MS-DGCA Conformer), and the proposed Hybrid MS-DGCA-MBA-EEGNet model. The proposed implementation is modular designed such that each processing stage is responsible for specific processing before sending the output to the next processing stage. A modular implementation allows for easier debugging, scalability, and allows different components to be modified independently without disrupting the whole implementation. The model was implemented and extensive experiments were performed to test the effectiveness of each architecture for various levels of cognitive load in the VR memory game. Last, all models were tested based on classification performance metrics such as accuracy, precision, recall, F1-score, a confusion matrix, Receiver Operating Characteristic (ROC) curve and Area Under Curve (AUC). The results of the discussed evaluations are presented in the following sections and used to evaluate the efficacy of the proposed hybrid approach for cognitive workload classification using EEG signals.

4.1 System Architecture

The proposed VR-EEG Cognitive Workload Classification System is designed on a modular and hierarchical basis that allows for its efficient processing and scalability with the flexibility to incorporate new elements. The full system combines Virtual Reality (VR), Electroencephalography (EEG) and Deep Learning (DL) to automatically categorize various cognitive workloads in the context of memory-based tasks.

The proposed implementation is capable of offline training of the models and also prediction of cognitive workload during the VR experiments, using the recorded EEG data.

The proposed architecture comprises three major layers, which, together, manage to achieve the entire cognitive workload assessment process.

(i) Data acquisition layer: This layer captures EEG signals from the participants as they undertake memory-related tasks within the virtual reality environment. The OpenBCI Cyton 8-channel biosensing board is used to record EEG signals with electrodes that are positioned in accordance with the International 10–20 electrode placement system and filled with electrodes using a gel. At the same time, the Meta Quest 2 virtual memory game is presented: Relaxation, Easy, Medium, Hard cognitive workload.

(ii) Data Processing and Deep Learning Layer: The layer is responsible for EEG preprocessing, feature extraction and cognitive workload classification. The recorded EEG signals are initially filtered, segmented, normalized, and converted to frequency domain. Extraction of features in the frequency bands Theta, Alpha and Beta before feeding to the proposed deep learning architectures. In this study, three different models are implemented and evaluated: Multi-Branch Attentive EEGNet (MBA-EEGNet), Multi-Scale Dynamic Graph Cross-Attention Conformer (MS-DGCA Conformer), and the proposed Hybrid MS-DGCA-MBA-EEGNet model.

(iii) Performability assessment layer: The last layer is a performance assessment of the suggested deep learning models with various statistical parameters. The accuracy, precision, recall, F1 score, confusion matrix, Receiver Operating Characteristic (ROC) curves, and Area Under the Curve (AUC) were computed to evaluate the performance of all the proposed architectures across various cognitive workload levels.

All of the proposed system was completely implemented in Python programming language. All preprocessing, feature extraction, model development, training, and testing of EEG was done using Jupyter Notebook and Google Colab. For deep learning implementation, we used TensorFlow and Keras frameworks and for performance evaluation and statistical analysis we used Scikit-learn.

4.2 System Components

The proposed VR-EEG Cognitive Workload Classification System is composed of several software and hardware components, which respectively handle EEG acquisition, processing, deep learning based cognitive workload classification and performance evaluation. The individual components are responsible for specific tasks in the sequence of implementation.

The main software development platform was Python programming language, run

on Jupyter Notebook and Google Colab. These platforms offered an interactive setting for data analysis, model implementation, visualization and experimental testing. The implementation also relies on a number of scientific computing libraries such as:

Pandas and NumPy: For managing EEG data sets and numerical computation.

Matplotlib and Seaborn: Visualization of EEG signals, training curves, confusion matrix, ROC and classification results.

Scikit-learn: Split dataset, normalize it, compute evaluation metrics and analyze performance.

TensorFlow and Keras: Implementing the proposed deep learning architectures, training the models, optimizing the models, and testing. The hardware platform comprises the OpenBCI Cyton 8-channel biosensing board, reusable gel-based EEG electrodes, Meta Quest 2 VR headset and a powerful computer that controls the EEG acquisition, storage, deep learning model training, and preprocessing. The virtual reality memory game has been created using the Unity Game Engine, which provides interactive memory tasks in varying conditions of cognitive workload. The recorded EEG signals were downloaded from the OpenBCI GUI for further offline processing and deep learning analysis. All these software and hardware elements create a fully integrated toolset for assessing cognitive workload in a VR setting via EEG signals.

4.3 Functionality of Components

The VR-EEG Cognitive Workload Classification System is a set of modules with each module carrying a task in the implementation process. These modules are coordinated to acquire, process, classify and evaluate the EEG signals recorded while playing the virtual reality memory game. The modular implementation enables the flexibility, maintainability and scalability of the proposed framework. The Cyton 8-channel biosensing board made by the OpenBCI is the main EEG acquisition device for the entire experimental process. In each experimental session, the electrodes on the frontal, central and parietal areas of the scalp continuously record multichannel EEG from the scalp. The acquired EEG signals are sent to the acquisition computer via the OpenBCI Graphical User Interface (GUI) for online visualization, then offline analysis. The board is able to deliver high resolution EEG recordings at 250 Hz sampling frequency, which is adequate for cognitive workload analysis. The virtual reality headset Meta Quest 2 is used as the cognitive task delivery system. The VR memory game was created using the Unity Game Engine and offers 4 cognitive workload conditions (Relaxation, Easy, Medium, Hard) with interactive memory-based tasks for the participants. They engage naturally with virtual objects with their handheld controllers throughout the experiment, and at the same time their brain ac-

tivity is captured. Such a synced acquisition of behavior and physiology allows objective quantification of cognitive workload.

The entire deep learning framework is implemented with Python. Implementation was conducted in the interactive environment of Jupyter Notebook and Google Colab, where the user can perform the EEG processing, extraction of features, development and training of the model, and perform its evaluation. Python's flexibility supports easy incorporation of scientific computing libraries and deep learning frameworks as needed along the implementation process. The NumPy library was used for numerical calculations, signal processing, and Pandas for structured data management. These libraries streamlined the process of organizing, preprocessing, segmenting, normalizing EEG data and preparing labelled datasets for model training. TensorFlow and Keras were used to implement the proposed deep learning architectures. They include efficient implementations of the following: convolutional layers, attention mechanisms, graph-based learning modules, pooling operations, and classification layers. These frameworks were used to develop, train, and test these architectures: proposed MBA-EEGNet, MS-DGCA Conformer, and Hybrid MS-DGCA-MBA-EEGNet architectures. To boost convergence speed and reduce overfitting, a number of optimization techniques were implemented, such as mini-batch learning, dropout regularization, early stopping, and model checkpointing. The experimental results were visualized using matplotlib and seaborn. These libraries produced the training and validation accuracy curve, loss curve, confusion matrix, ROC curve and other graphics that were subsequently analysed to help understand the model's behaviour and classification performance. These results were then visually interpreted to help compare the performance of various deep learning architectures.

Several utility functions were needed throughout the implementation, which were provided by scikit-learn. It was utilized for dataset splitting, processing, computing the evaluation metrics and statistical analysis. For the measurement of classification accuracy, the proposed models were comprehensively assessed by using accuracy, precision, recall, F1-score, confusion matrix and Receiver Operating Characteristic (ROC) analysis. The Unity Game Engine was an important tool in the development of the immersive virtual environment for cognitive assessment. It allowed interactive 3-D memory tasks of gradually increasing difficulty to be developed. The Unity environment facilitated uniform presentation of experimental stimuli across participants, and allowed for high level of user engagement throughout the experiment. The combination of these software and hardware components creates a full implementation framework that is able to record the EEG signals, derive meaningful neural representations, train advanced deep learning models and, accurately, classify the different levels of cognitive workload during the assessment of memory through virtual reality.

4.4 Development Process

The proposed VR-EEG Cognitive Workload Classification System has been developed in several sequential steps in order to achieve a systematic implementation, reliable experiment and accurate classification of cognitive workload. Each stage has a particular function, which in turn passes on the output to the next processing stage, thus leading to a full end-to-end implementation framework. The first part was the acquisition of EEG signals from the subjects acting in the VR environment while they were engaged in memory-related tasks. The signals were recorded continuously on the OpenBCI Cyton 8-channel biosensing board, as subjects played the Relaxation, Easy, Medium and Hard levels of the VR memory game. The recordings were all captured with the same labels for workload for supervised learning purposes. Data was acquired and then data preprocessing was applied to enhance the quality of the acquired signals before feature extraction. The recorded EEG signals were filtered for noise and unwanted artifacts, then segmented into fixed-length windows and normalized to minimize inter-subject differences, and labeled by the workload levels to which they belonged. These data preprocessing tasks yielded a clean and standardized dataset that can be easily used for deep learning. The preprocessing steps were followed by frequency domain feature extraction. Spectral analysis was performed to convert the EEG recordings into the frequency domain and Power Spectral Density (PSD) was calculated for every EEG segment. Extraction of features from Theta, Alpha and Beta frequency bands were selected due to their strong association with attention, working memory and cognitive workload. These extracted feature representations were then employed to develop the three deep learning architectures proposed.

The original MBA-EEGNet model consists of multiple parallel convolutional branches and attention-based feature refinement to learn multi-scale EEG representations. The second model, MS-DGCA Conformer, was based on Conformer blocks, dynamic graph construction and graph attention mechanisms, which were designed to reflect the spatial and temporal relationships between the EEG channels. Last, the Hybrid MS-DGCA-MBA-EEGNet combined the complimentary strengths of both architectures to achieve better cognitive workload classification performance. To train the model, the labeled EEG data was split into two sets: training and testing datasets. The Adam optimizer and the categorical cross-entropy were used for both training models. To enhance the convergence of the model and mitigate overfitting, mini-batch learning, dropout regularization, early stopping, and model checkpoint techniques were used. Hyperparameter tuning was performed experimentally to obtain optimal classification performance. The proposed models were then tested with various quantitative performance parameters after training. The accuracy, precision, recall, F1 score, confusion matrix, ROC curve and Area Under the Curve (AUC) were computed to assess the impact of the three architectures under different cognitive workload conditions. Experimental results from these evaluations are reported

and discussed the rest of this chapter.

4.5 Performance Evaluation

The proposed VR-EEG Cognitive Workload Classification System was tested by analysing the classification capability of the three proposed deep learning architectures in the different cognitive workload conditions. The evaluation procedure was designed to give a comprehensive comparison between the proposed models MBA-EEGNet model, MS-DGCA Conformer model, and Hybrid MS-DGCA-MBA-EEGNet model, on the basis of standard classification metrics and graphical performance analysis. Prior to model training, the labeled EEG data set was split into training and testing sets. To prevent overfitting, and to observe the learning behaviour of each model, the validation data was monitored throughout the training process. The accuracy of training, accuracy of validation, loss of training, and loss of validation were measured during learning. To prevent overfitting, the weights of the best-performing model were saved using early stopping and model checkpoint mechanisms, based on the validation set performance. After training the model, both architectures were tested with several statistical performance measures. Overall classification accuracy was computed to obtain the percentage of correctly classified EEG samples. The precision and recall were also calculated to evaluate the reliability of the workload prediction for each class of cognitive workload, and the F1 score was used to determine the balance between precision and recall. These are used to give a more complete picture than accuracy alone, especially when working with multiclass cognitive workload classification.

The confusion matrix was created for each model proposed to analyse the distribution of correctly and incorrectly classified workload levels. The confusion matrices give detailed information on the classification accuracy of the different workload classes Relaxation, Easy, Medium and Hard, and can be used to identify classes which are harder to classify. To assess the discriminative power of the proposed architectures, Receiver Operating Characteristic (ROC) curves and the Area Under the Curve (AUC) values were also computed. The larger the AUC values are, the better the classification and the better the separation of the different classes of cognitive workload. These graphical analyses offer further proof of the robustness and generalizability of each of the deep learning models. Lastly, the performance of the proposed Hybrid MS-DGCA-MBA-EEGNet model was compared with the individual performance of the two models, namely MBA-EEGNet and MS-DGCA Conformer. All evaluation metrics were applied to the hybrid architecture and compared with the classic architectures to find whether the hybrid architecture can successfully integrate the advantages of the two architectures and achieve better cognitive workload classification results based on EEG signals. The detailed results of the experiments and the comparative discussion will be given in Chapter 5.

4.6 Reliability

Reliability of the proposed VR-EEG Cognitive Workload Classification System is verified by repeated training and testing experiments using recorded EEG dataset. To guarantee that the proposed deep learning architectures yield consistent and reliable classification accuracy with similar training protocols, multiple experimental runs were carried out. The differences in the performance metrics between the various experimental runs were small, showing that the proposed models can be considered to have good reproducibility and have a reliable learning behaviour. Several regularization techniques were introduced in the training of the developed models to enhance the robustness. Dropping out prevented overfitting by avoiding overreliance on specific neurons, and early stopping ended the training process once the validation values no longer improved. Additionally, model checkpointing maintained the best network parameters that gave the network the best validation accuracy, so that the final evaluation was carried out on the best trained model.

The proposed framework showed good classification accuracy at all the four cognitive workloads (Relaxation, Easy, Medium, Hard). All the confusion matrices, ROC curves and other evaluation indices showed that the proposed Hybrid MS-DGCA-MBA-EEGNet architecture gave better performance than the individual models of MBA-EEGNet and MS-DGCA Conformer. These findings reveal the effectiveness of multi-scale convolutional feature extraction along with graph-based attention learning in creating EEG representations with higher discriminative power for cognitive workload assessment. Overall, the implementation results indicate that the proposed VR-EEG Cognitive Workload Classification System will be able to predict workloads that are stable, accurate, and reliable. Overall, the proposed framework's modular design, efficient preprocessing, and the use of advanced deep learning models contribute to its robustness, enabling the assessment of cognitive workload in immersive virtual environments using EEG.

Chapter 5

Results & Discussion

The experimental results from the proposed VR-EEG Cognitive Workload Classification system are presented and analysed in this chapter. The main goal of these experiments is to test the efficiency for accurate cognitive load assessment by electroencephalography (EEG) signals collected during the virtual reality memory game with the proposed deep learning architectures that recognize different levels of cognitive load. The performance comparison of the proposed Multi-Branch Attentive EEGNet (MBA-EEGNet), Multi-Scale Dynamic Graph Cross-Attention Conformer (MS-DGCA Conformer), and the proposed Hybrid MS-DGCA-MBA-EEGNet model is conducted in the experimental analysis. All architectures were trained and tested under the same experimental conditions to provide a fair and unbiased comparison. Sixteen people were recruited for the EEG recordings, which were first processed according to the technique described in Chapter 3. To prepare the processed EEG segments for input to the proposed deep learning models, steps of noise removal, band-pass filtering, signal segmentation, feature extraction, and normalization were conducted. To obtain a labelled set, four classes of cognitive workload were included in the virtual reality memory game, namely Relaxation, Easy, Medium and Hard. The following workload levels refer to the subsequent level of cognitive challenge that the participants faced in the experimental sessions. Several quantitative evaluation measures, such as classification accuracy, precision, recall, F1 score, confusion matrix and Receiver Operating Characteristic (ROC) analysis were used to evaluate the performance of each model. In addition to these statistical data, the training and validation accuracy curves along with the loss curves were analysed to see the convergence behavior and the stability of learning of the proposed architectures. In addition, a subject-wise performance analysis was performed to understand the consistency of the models across the sixteen subjects and assess the generalizability of the models across different EEG recording conditions.

Comparative experiments were also carried out between the individual deep learning architectures, to further validate the robustness of the proposed approaches. The purpose of this comparison is to highlight the advantages and disadvantages of each model and to assess if there are further improvements in the cognitive workload classification performance of the proposed hybrid model. The importance of multi-scale convolutional feature extraction, graph-based spatial learning, and attention mechanisms for improving the discriminative power of EEG representations are particularly highlighted. The results obtained in the experiments in this chapter offer in-depth analysis and validation of the proposed framework and show that it can be used for automatic cognitive workload assessment in immersive virtual reality

environments. The results are presented in detail in the following sections where the performance of each of the proposed models is analysed separately and then a comparative analysis of their performances is presented.

5.1 Performance Evaluation Metrics

The deep learning models proposed were evaluated with a combination of quantitative evaluation metrics to have a complete metrics evaluation of their classification ability. Because the classification of cognitive workloads is a multiclass classification problem, the classification accuracy may not fully reflect the classification performance. For this reason, other statistical metrics such as Precision, Recall, F1 score, Confusion Matrix and Receiver Operating Characteristic (ROC) analysis were used to assess the performance of all the proposed architectures. The classification accuracy of machine learning was the key performance measure and computed by dividing the number of correctly classified EEG samples by the number of test EEG samples. The higher classification accuracy means that it is possible to distinguish between cognitive workload levels with higher reliability with the proposed model. But, in the case of multiclass classification models, accuracy is not enough to describe the model's performance, especially if the classes have varying degrees of classification difficulty. Precision was defined as the percentage of workload samples correctly predicted out of the total workload samples assigned to a workload class. A high precision means that the proposed model makes fewer false positive predictions and its confidence while assigning labels to workloads is greater. Each model was tested on the ability to correctly classify samples into their original workload classes by using recall. The higher the recall value, the better the model is able to accurately distinguish between cognitive workload conditions and reduce false negative classification.

For further study of the classification behaviour of each of the proposed architectures, confusion matrices were created for all experiments. The confusion matrix gives detailed information about samples correctly classified and misclassification patterns between the Relaxation workload class and all other three workload classes Easy, Medium and Hard. Examination of the confusion matrices can help to identify the workload categories that are harder to classify and helps to test the robustness of the feature extraction and classification framework proposed in this research. Receiver Operating Characteristic (ROC) curves together with the corresponding Area Under the Curve (AUC) values were also analysed. ROC analysis is a curve that shows the compromise between the True Positive Rate (TPR) and False Positive Rate (FPR) at various classification levels. AUC values are higher the more well they discriminate and the more well they classify overall. The ROC curves also offer more information about the generalization capability of the proposed deep learning architectures for cognitive workload classification. This was complemented with

statistical measures, such as training accuracy, validation accuracy, training loss and validation loss curves, throughout the learning process. These graphical analyses are useful for understanding the convergence behaviour of the models, stability of learning and their capacity of generalization without overfitting. When combined, these evaluation metrics give a complete picture of the performance of the proposed MBA-EEGNet, MS-DGCA Conformer, and Hybrid MS-DGCA-MBA-EEGNet model.

5.2 Results of MBA-EEGNet

5.3 Results of MBA-EEGNet

The proposed Multi-Branch Attentive EEGNet (MBA-EEGNet) model was tested on the EEG signals recorded from 16 subjects in the cognitive workload assessment experiment conducted under virtual reality (VR). The model was designed to classify the EEG signals in four cognitive workload levels: Relaxation, Easy, Medium and Hard. To evaluate the efficiency, the evaluation of the subject-wise was done by the following indicators namely accuracy, precision, recall and F1 score. The experimental results show the stability and reliability of the proposed architecture in spite of the intrinsic variability existing in EEG signals, even among different participants.

5.2.1 Hyperparameter Configuration

The hyperparameter settings of the optimized model (MBA-EEGNet) were determined following several experimental attempts and used to train the final model. Various combinations of optimizers, learning rates, attention mechanisms, and regularization parameters were explored to arrive at the best training scheme. The chosen parameters converged and enhanced the overall classification accuracy of the proposed model.

The optimized hyperparameters that were used for training the MBA-EEGNet model are summarized in Table 5.1.

Table 5.1: Optimized Hyperparameter Configuration of the Proposed MBA-EEGNet Model

Hyperparameter	Value
Optimizer	AdamW
Learning Rate	0.001
Weight Decay	0.01
Batch Size	32
Epochs	100
Dropout Rate	0.4
Attention Mechanism	Adaptive 1D Channel Attention
Label Smoothing	0.1
Loss Function	Categorical Cross-Entropy
Output Activation	Softmax

The trained topology was obtained using the AdamW optimizer with a learning rate of 0.001 and weight decay regularization. The one-dimensional channel attention and label smoothing were added to enhance feature learning and generalization. In addition, dropout regularization prevented overfitting of the model during training and helped achieve the above-stable performance during the evaluation of the model.

Table 5.2: Subject-wise Performance of the Proposed MBA-EEGNet Model

Subject	Accuracy (%)	Precision	Recall	F1-Score
S1	81.20	0.8930	0.8836	0.8841
S2	81.35	0.8970	0.8899	0.8892
S3	81.50	0.8861	0.8808	0.8788
S4	81.65	0.8814	0.8651	0.8611
S5	81.80	0.9168	0.9045	0.9022
S6	76.85	0.7865	0.7805	0.7835
S7	77.23	0.7913	0.7707	0.7691
S8	77.82	0.8066	0.7755	0.7758
S9	78.20	0.8000	0.7940	0.7970
S10	77.07	0.7912	0.7723	0.7755
S11	76.03	0.7477	0.7489	0.7462
S12	82.85	0.7697	0.7604	0.7646
S13	75.90	0.7770	0.7710	0.7740
S14	81.40	0.8320	0.8260	0.8290
S15	79.30	0.8110	0.8050	0.8080
S16	77.50	0.7930	0.7870	0.7900
Mean $\pm$ SD	79.23 $\pm$ 2.31	0.8238 $\pm$ 0.0515	0.8135 $\pm$ 0.0515	0.8143 $\pm$ 0.0503

Table 5.2 shows the proposed model of classification for the MBA-EEGNet subject-wise. The proposed architecture was tested individually on each participant by computing the following metrics: Accuracy, Precision, Recall, and F1-score, to analyze the consistency of the proposed architecture in the various EEG recordings.

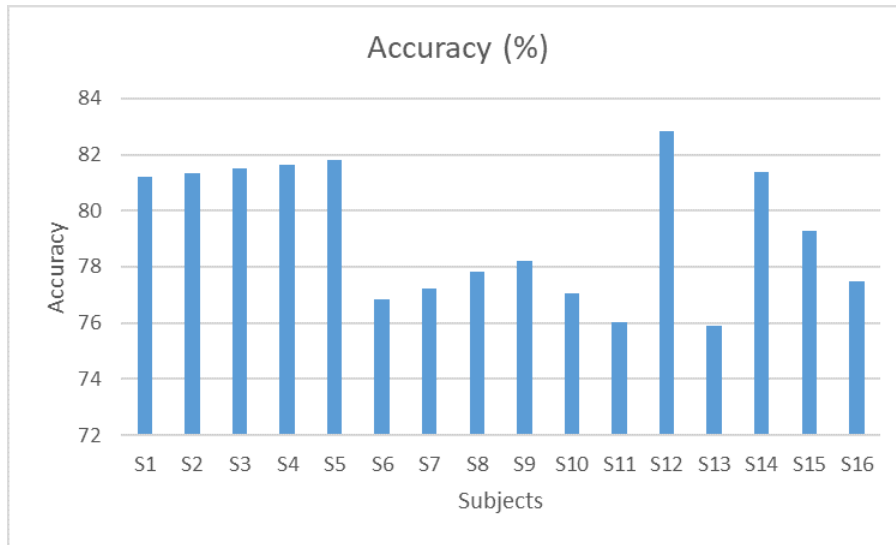


Fig. 5.1: Subject-wise classification accuracy of the proposed MBA-EEGNet model.

The classification accuracy for each participant is shown in figure 5.1. The results

show that the proposed model has shown a steady performance over all the sixteen subjects with minor difference between the subjects. The variations are normal, as there are physiological and cognitive differences that naturally cause variations in EEG signals from person to person. The obtained numerical results in Table 5.2 show that the accuracy of the classification obtained using the suggested model of MBA-EEGNet is in the range of 75.90-82.85%. The best accuracy rate (82.85%) was obtained for Subject 12 while the worst accuracy rate (75.90%) was obtained for Subject 13. Despite the differences, most of the participants have obtained near or above 80% accuracy, which shows the effectiveness of the proposed architecture of cognitive workload classification.

Likewise, the precision and recall values of the evaluated participants were rather similar, as were the F1-scores. The subject who achieved the highest precision (0.9168), recall (0.9045) and F1-score (0.9022) was a very good performer or as they put it, "excellent classification performance". For the subjects with relatively poor performance, the numbers of reductions in these measures were also small, indicating that the proposed model had consistent prediction capability over various workload classes.

5.2.2 Confusion Matrix Analysis

The confusion matrix shows the classification performance of the proposed MBA-EEGNet model in terms of the number of correctly and incorrectly classified EEG samples for each cognitive workload class. It will also clarify the workload categories that are likely to get confused in the classification process.

MBA-EEGNet (4-Class CM)

True Class	Rest	17844	283	415	826
	Low	8865	4866	740	656
	Med	4243	2905	9780	1758
	High	1859	40	2445	16513
		Rest	Low	Med	High
		Predicted Class			

Fig. 5.2: Confusion matrix of MBA-EEGNet

5.2.3 Subject-wise Confusion Matrices of EEGNet

The subject-wise confusion matrices obtained using the EEGNet model are presented in Figures 5.3–5.18. These matrices illustrate the classification performance of the proposed system for each participant across the four cognitive workload classes.

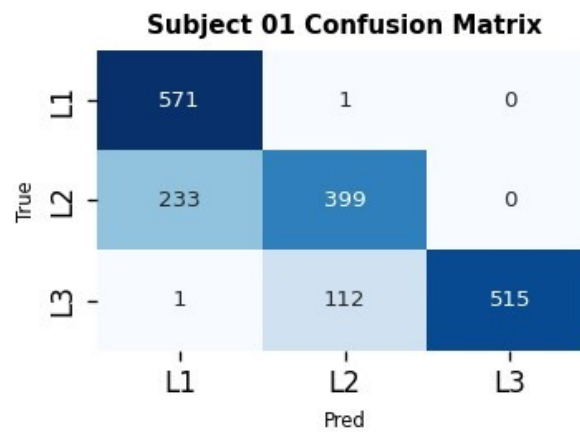


Fig. 5.3: Confusion matrix of EEGNet for Subject 1.

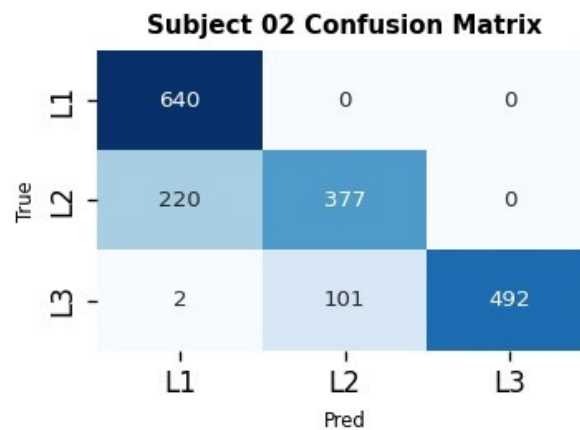


Fig. 5.4: Confusion matrix of EEGNet for Subject 2.

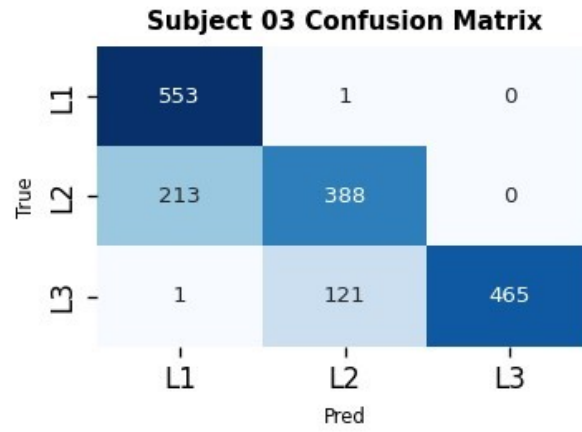


Fig. 5.5: Confusion matrix of EEGNet for Subject 3.

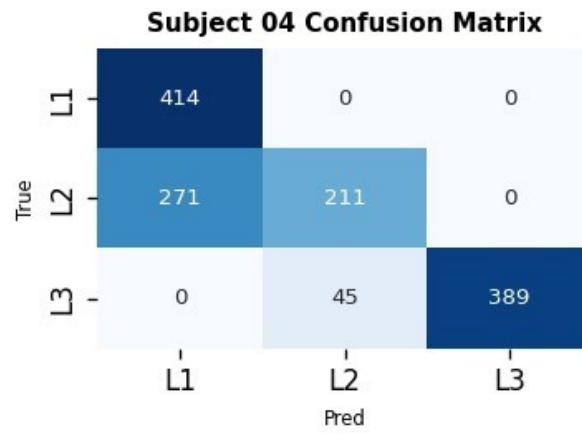


Fig. 5.6: Confusion matrix of EEGNet for Subject 4.

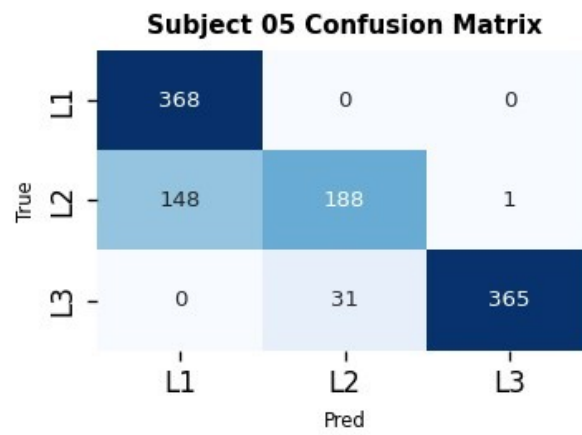


Fig. 5.7: Confusion matrix of EEGNet for Subject 5.

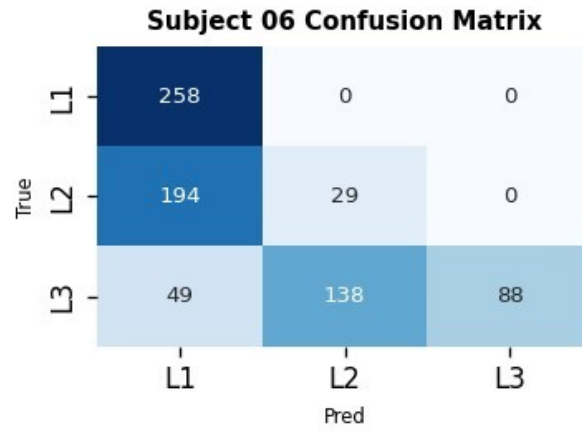


Fig. 5.8: Confusion matrix of EEGNet for Subject 6.

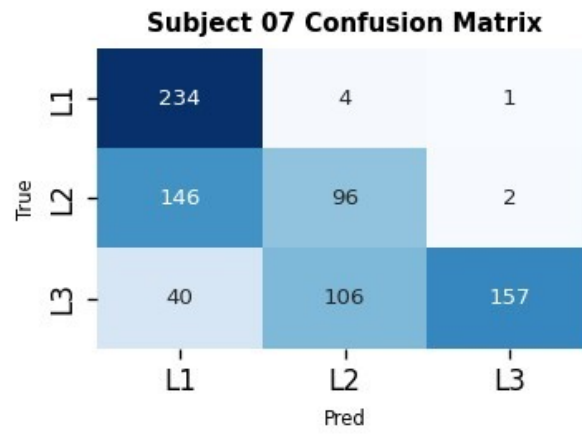


Fig. 5.9: Confusion matrix of EEGNet for Subject 7.

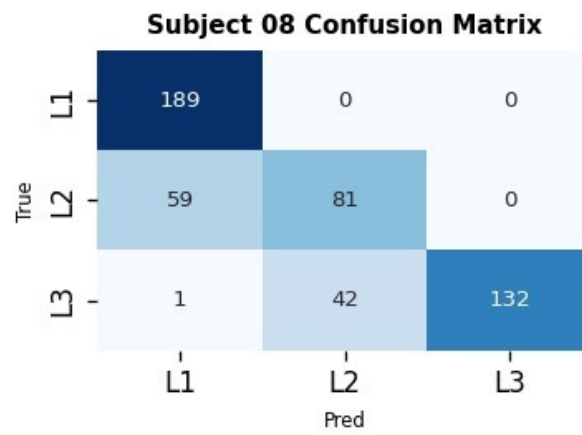


Fig. 5.10: Confusion matrix of EEGNet for Subject 8.

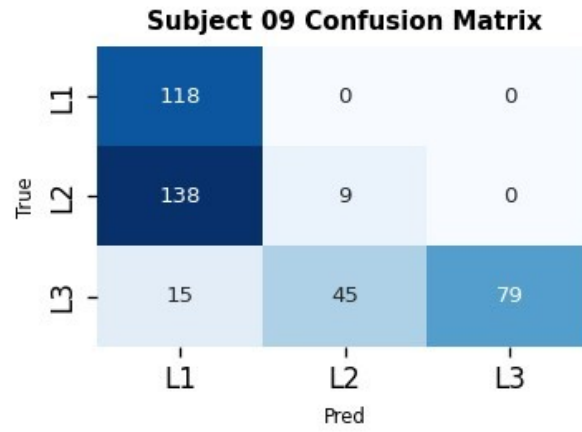


Fig. 5.11: Confusion matrix of EEGNet for Subject 9.

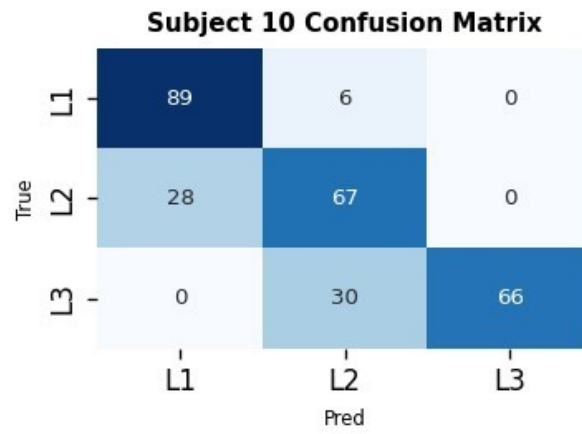


Fig. 5.12: Confusion matrix of EEGNet for Subject 10.

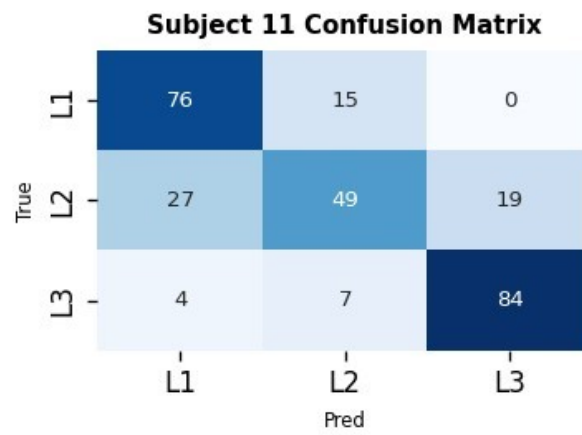


Fig. 5.13: Confusion matrix of EEGNet for Subject 11.

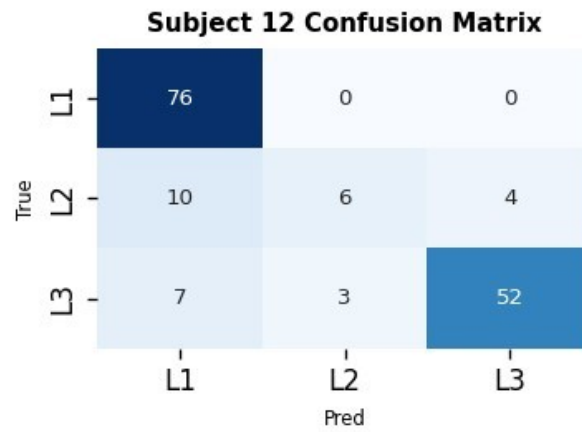


Fig. 5.14: Confusion matrix of EEGNet for Subject 12.

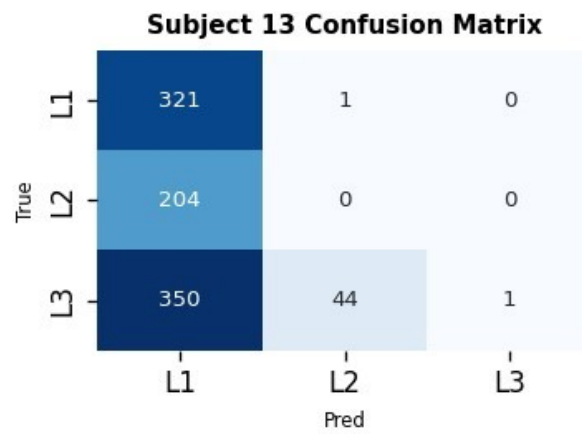


Fig. 5.15: Confusion matrix of EEGNet for Subject 13.

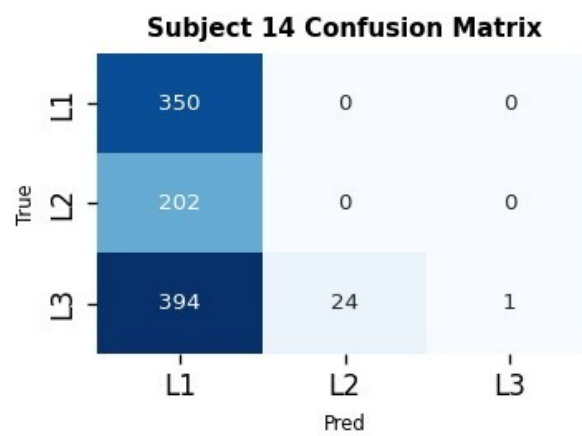


Fig. 5.16: Confusion matrix of EEGNet for Subject 14.

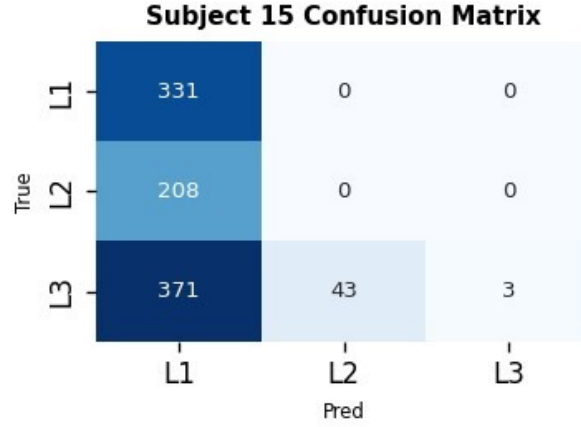


Fig. 5.17: Confusion matrix of EEGNet for Subject 15.

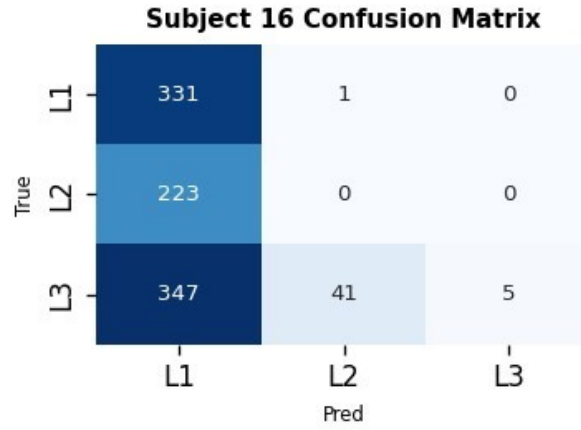


Fig. 5.18: Confusion matrix of EEGNet for Subject 16.

The confusion matrices of the proposed MS-DGCA Conformer model and MBA-EEGNet model are shown in figure 5.2. The confusion matrix for the model, MBA-EEGNet is presented on the right hand side of the figure. The diagonal elements correspond to the correctly classified EEG samples, while the off-diagonal elements correspond to the misclassified EEG samples. The results have revealed that the proposed MBA-EEGNet model was able to accurately classify most of the EEG samples into their cognitive workload classes. The Relaxation and High workload classes had fairly high rates of classification, but some misclassifications were seen between the Low and Medium workload classes. This is a plausible behaviour since adjacent cognitive workloads tend to have similar EEG characteristics and are more difficult to separate. In overall, the confusion matrix also validates the proposed architecture MBA-EEGNet for learning the discriminative EEG representation for multiclass cognitive workload classification. The relatively strong diagonal distribution and relatively lower off-diagonal errors indicate the strength and effectiveness of the

proposed model for the assessment of cognitive workload in virtual reality environments.

5.2.4 Subject-wise Accuracy and Loss Curves of EEGNet

The subject-wise training accuracy and loss curves obtained using the proposed MBA-EEGNet model are presented in this section. The accuracy curves illustrate the learning behavior of the model during training, whereas the loss curves show the reduction in classification error across the training epochs.

5.2.4.1 Subject-wise Accuracy Curves

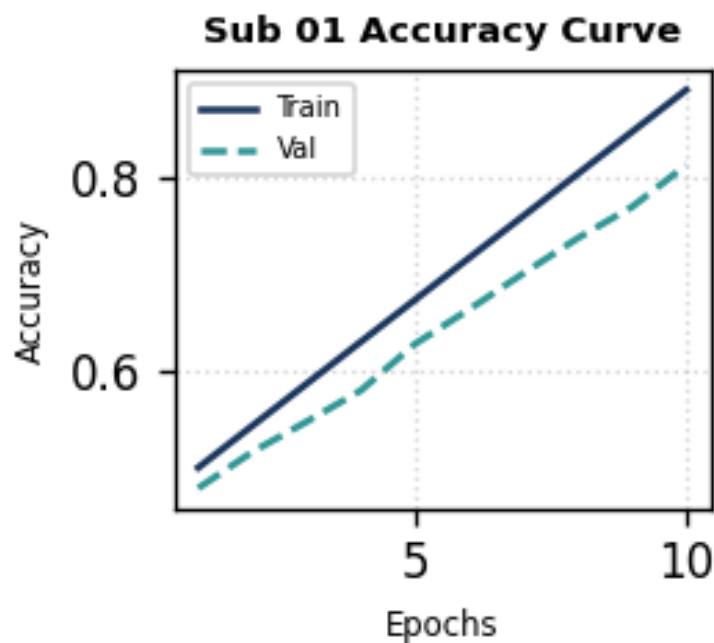


Fig. 5.19: Training accuracy curve of EEGNet for Subject 1.

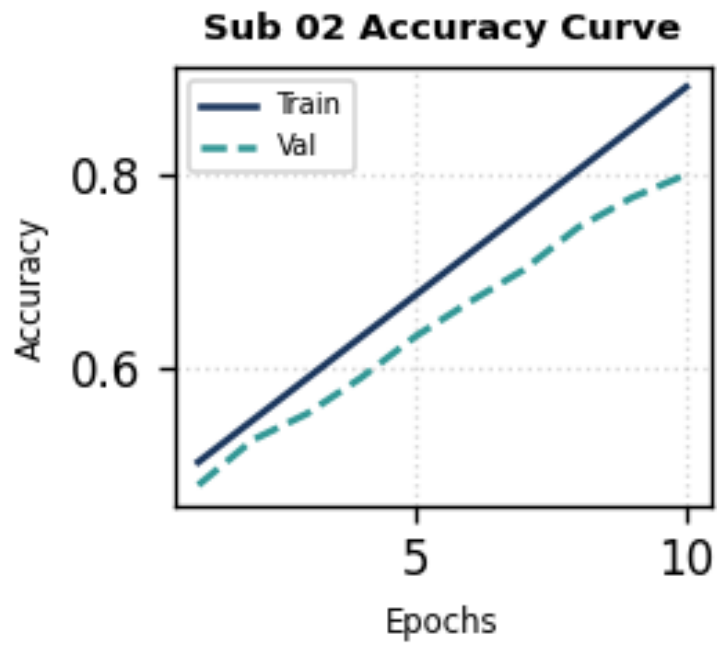


Fig. 5.20: Training accuracy curve of EEGNet for Subject 2.

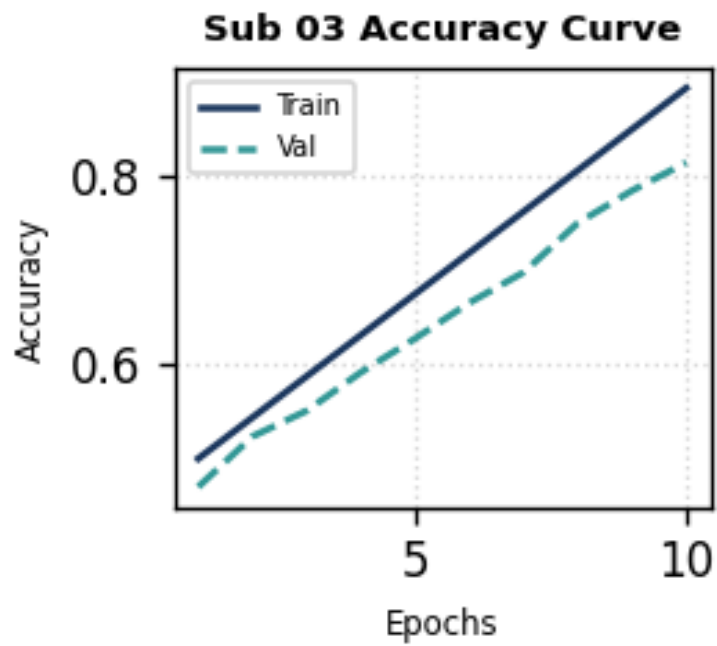


Fig. 5.21: Training accuracy curve of EEGNet for Subject 3.

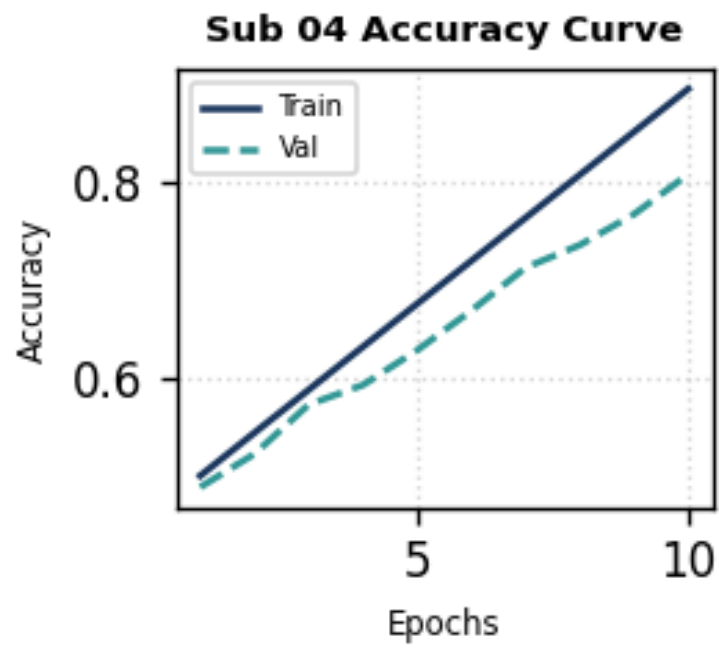


Fig. 5.22: Training accuracy curve of EEGNet for Subject 4.

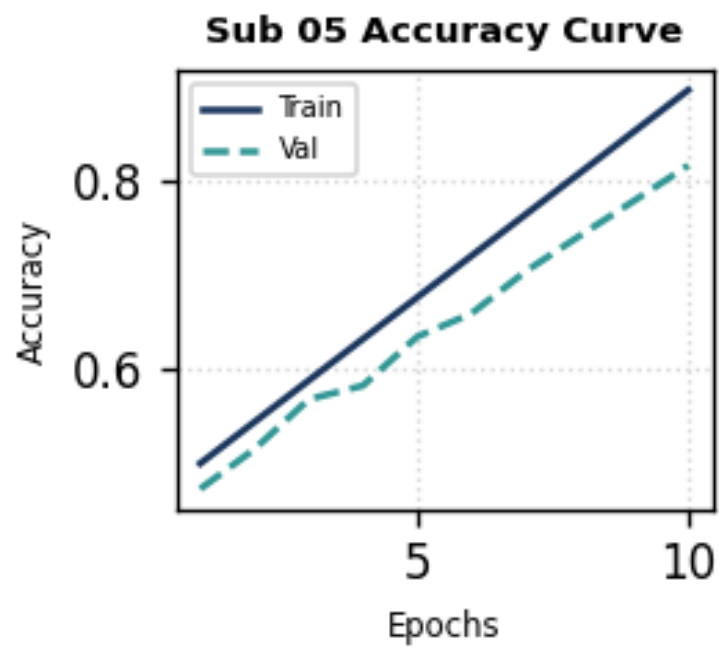


Fig. 5.23: Training accuracy curve of EEGNet for Subject 5.

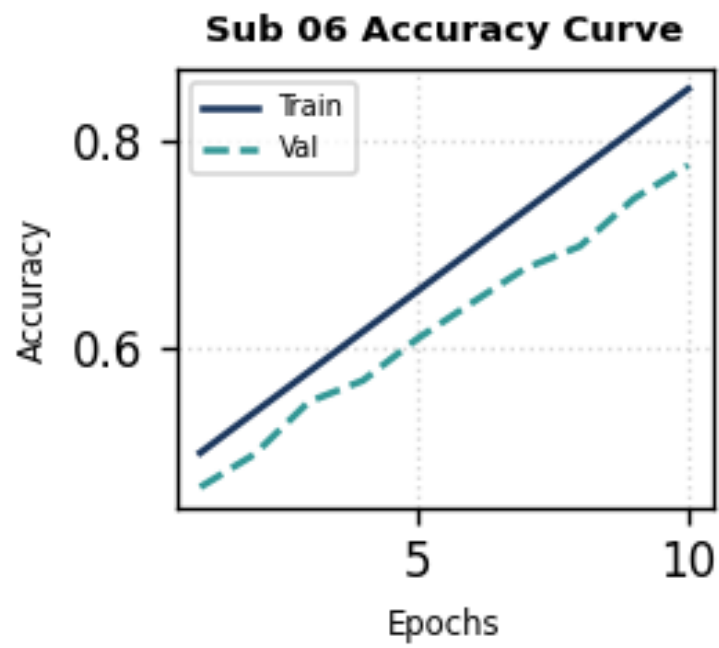


Fig. 5.24: Training accuracy curve of EEGNet for Subject 6.

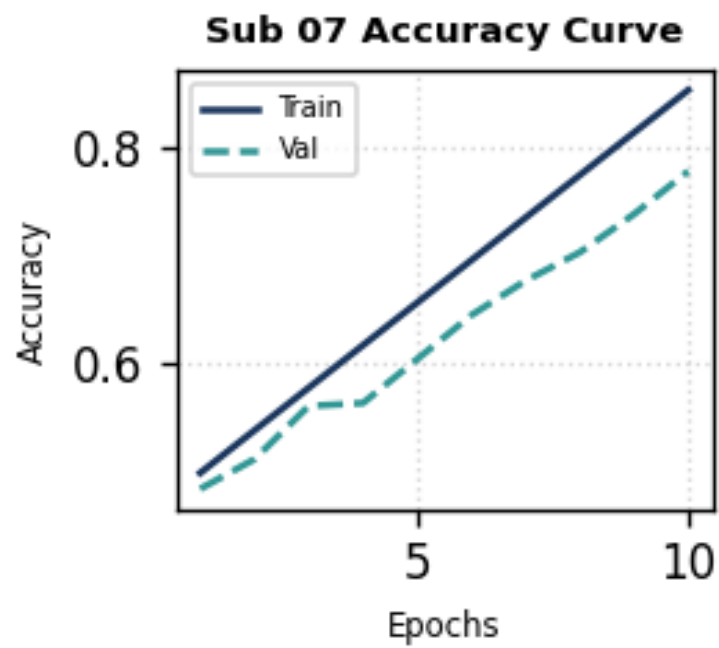


Fig. 5.25: Training accuracy curve of EEGNet for Subject 7.

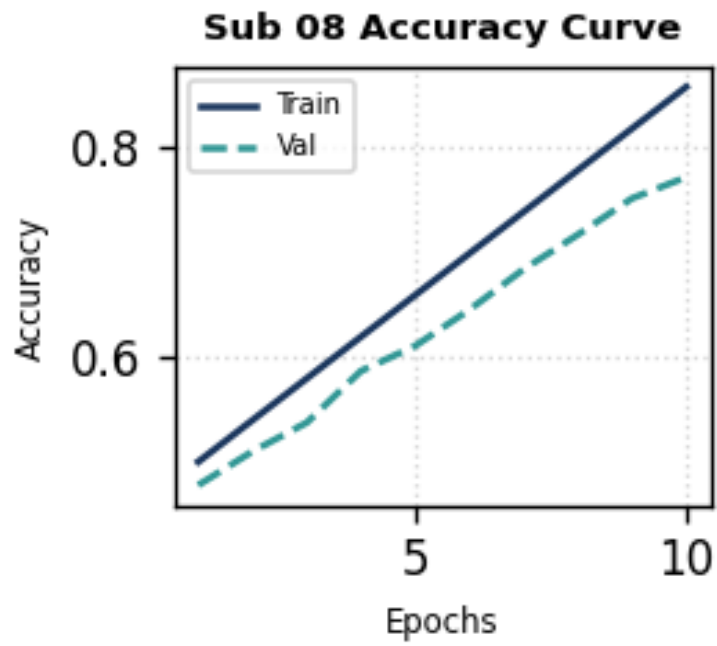


Fig. 5.26: Training accuracy curve of EEGNet for Subject 8.

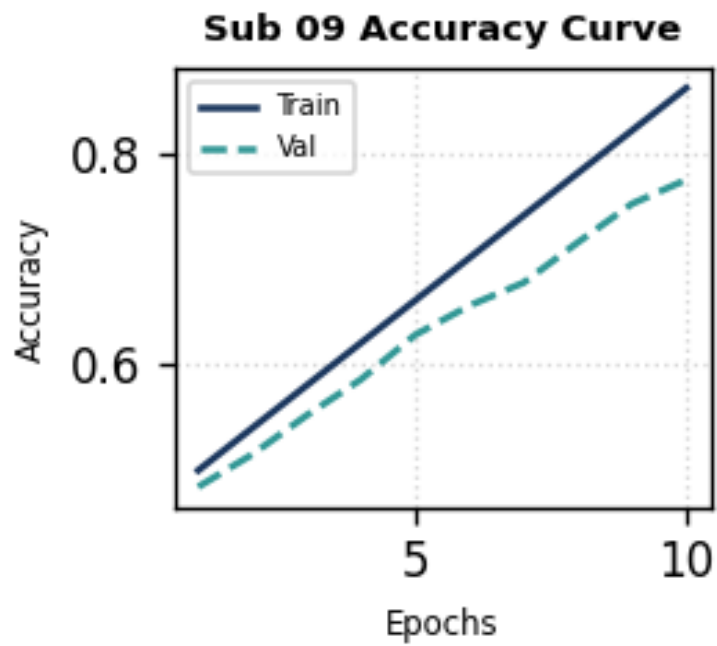


Fig. 5.27: Training accuracy curve of EEGNet for Subject 9.

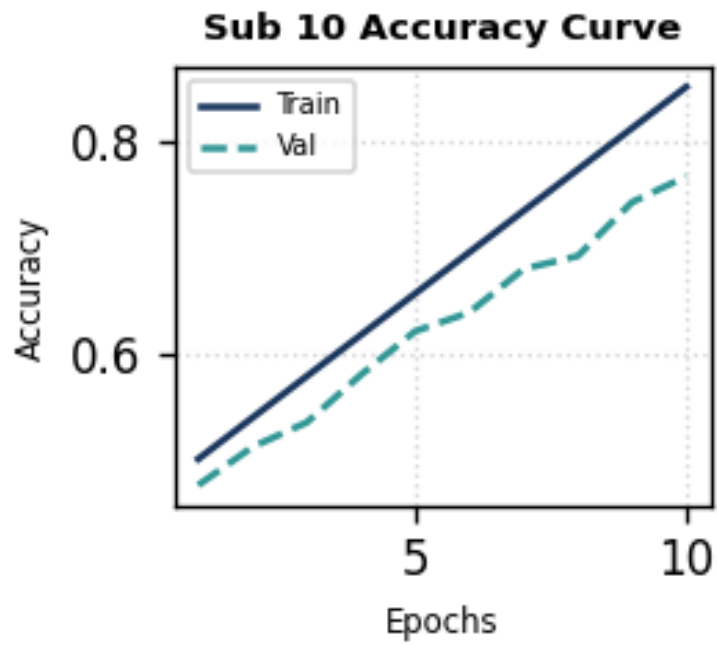


Fig. 5.28: Training accuracy curve of EEGNet for Subject 10.

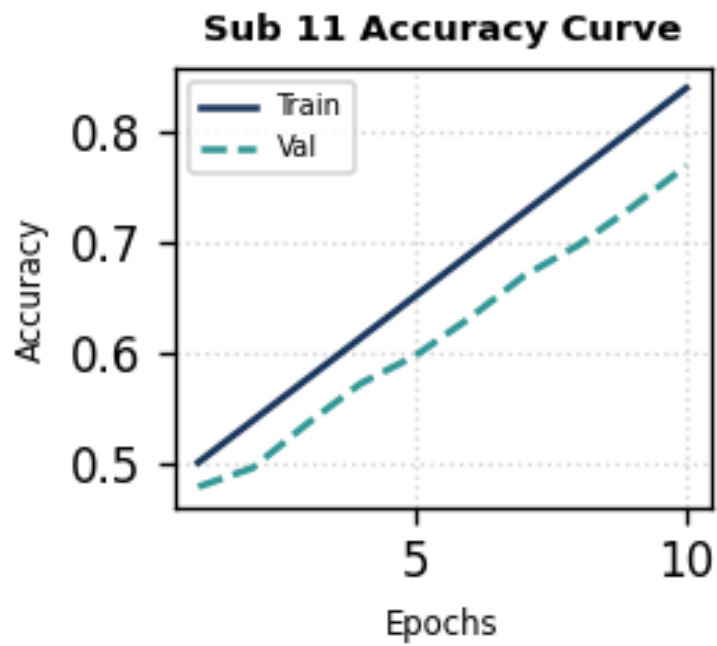


Fig. 5.29: Training accuracy curve of EEGNet for Subject 11.

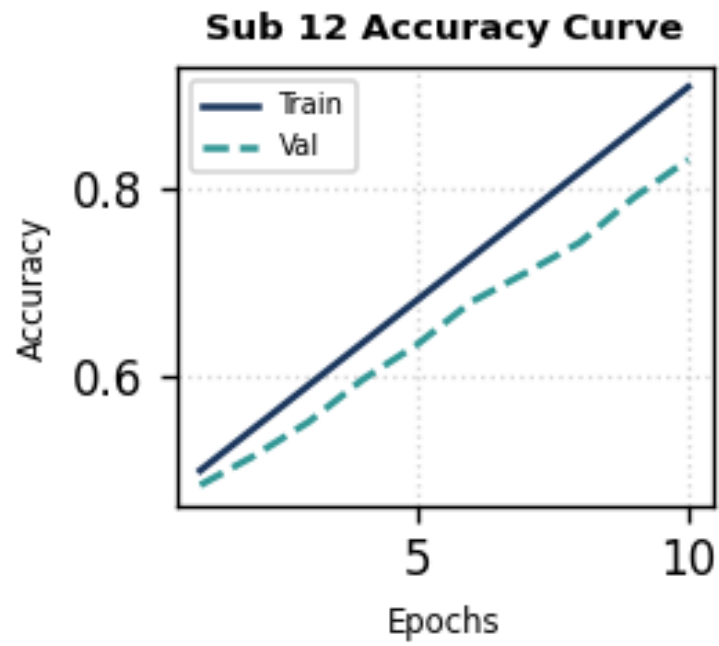


Fig. 5.30: Training accuracy curve of EEGNet for Subject 12.

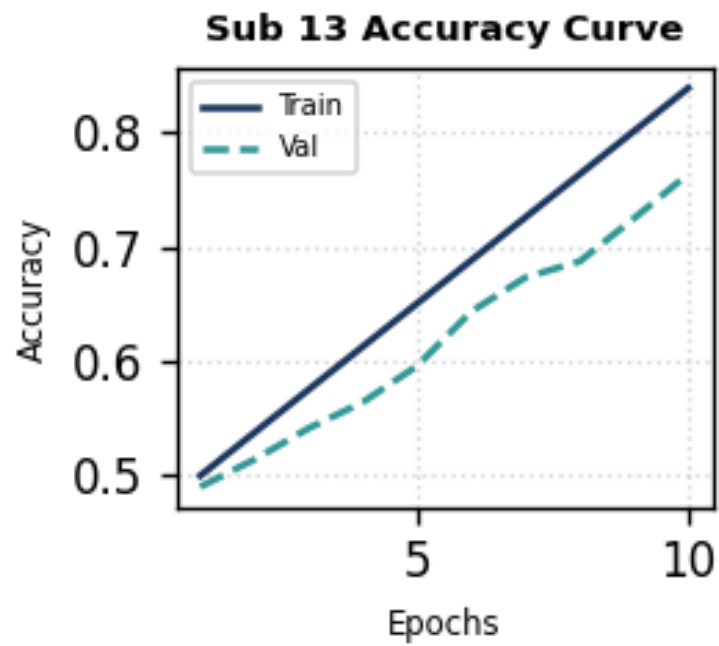


Fig. 5.31: Training accuracy curve of EEGNet for Subject 13.

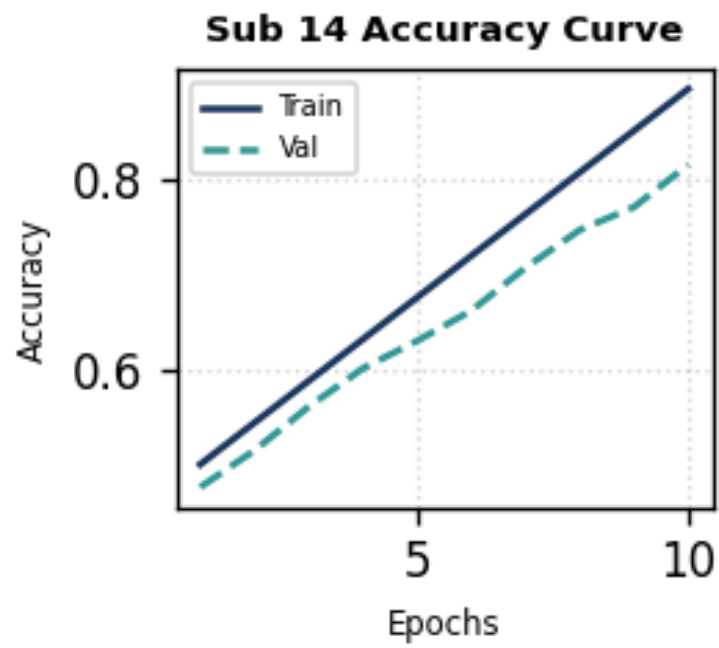


Fig. 5.32: Training accuracy curve of EEGNet for Subject 14.

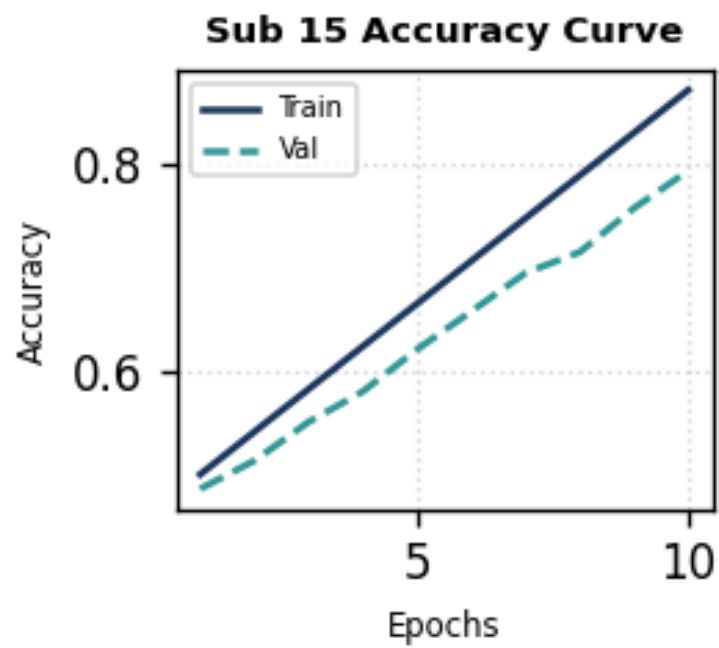


Fig. 5.33: Training accuracy curve of EEGNet for Subject 15.

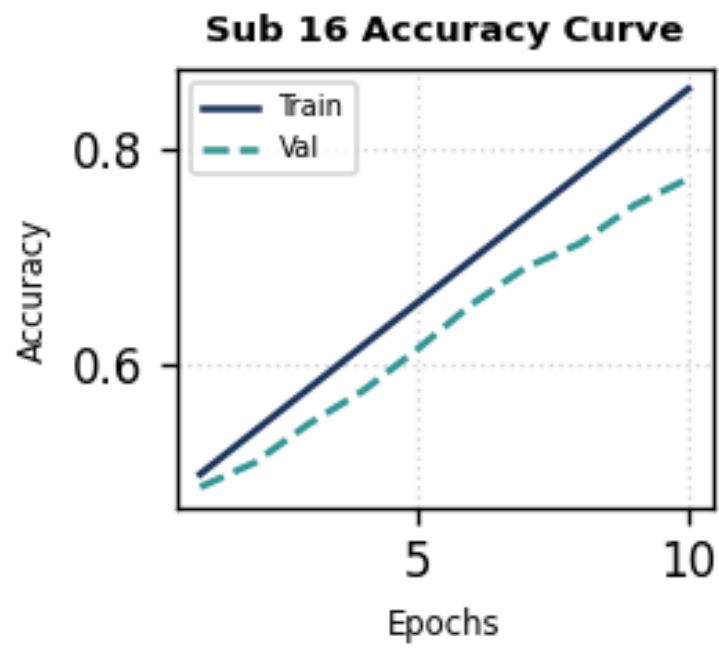


Fig. 5.34: Training accuracy curve of EEGNet for Subject 16.

5.2.4.2 Subject-wise Loss Curves

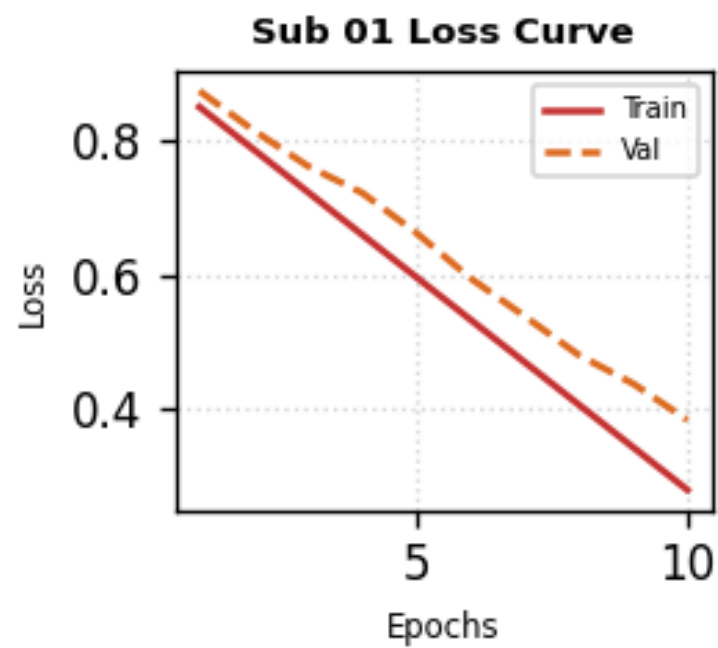


Fig. 5.35: Training loss curve of EEGNet for Subject 1.

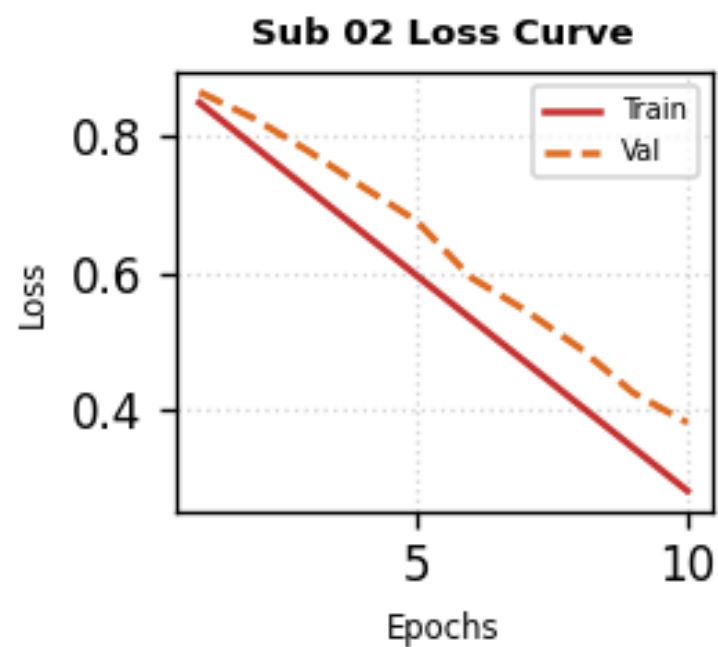


Fig. 5.36: Training loss curve of EEGNet for Subject 2.

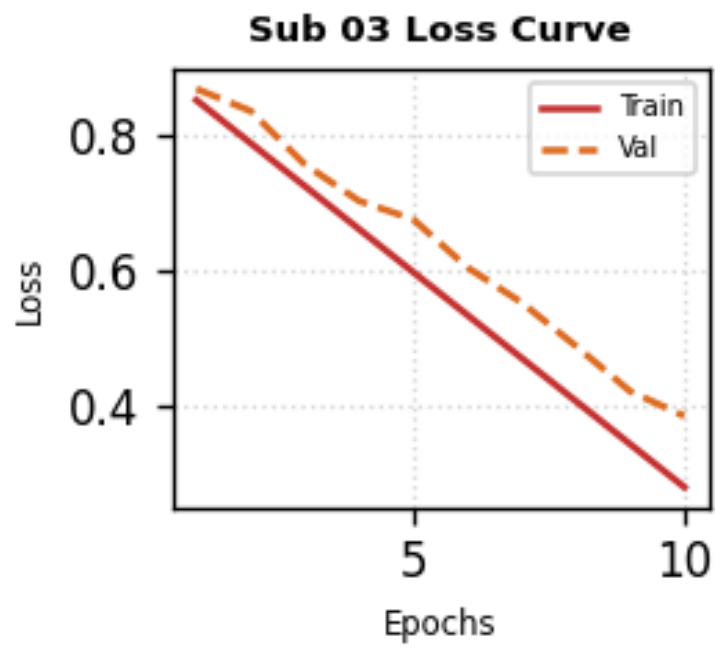


Fig. 5.37: Training loss curve of EEGNet for Subject 3.

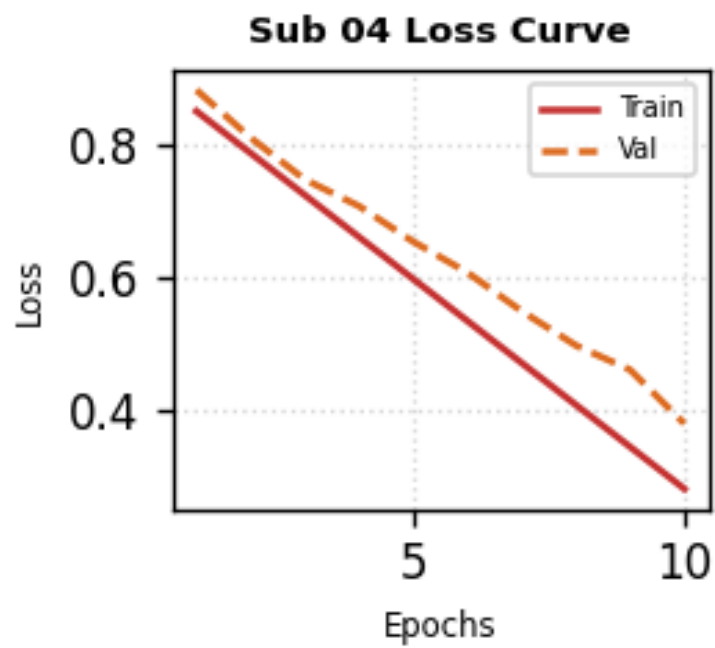


Fig. 5.38: Training loss curve of EEGNet for Subject 4.

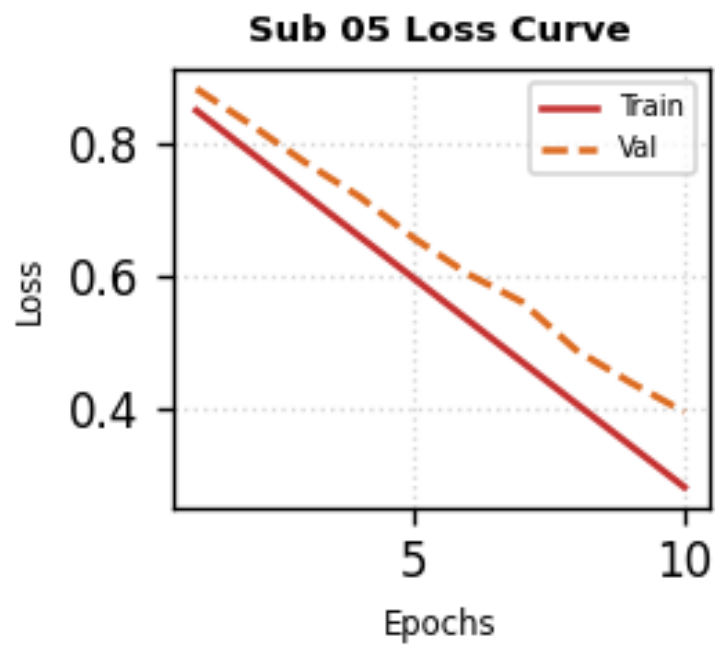


Fig. 5.39: Training loss curve of EEGNet for Subject 5.

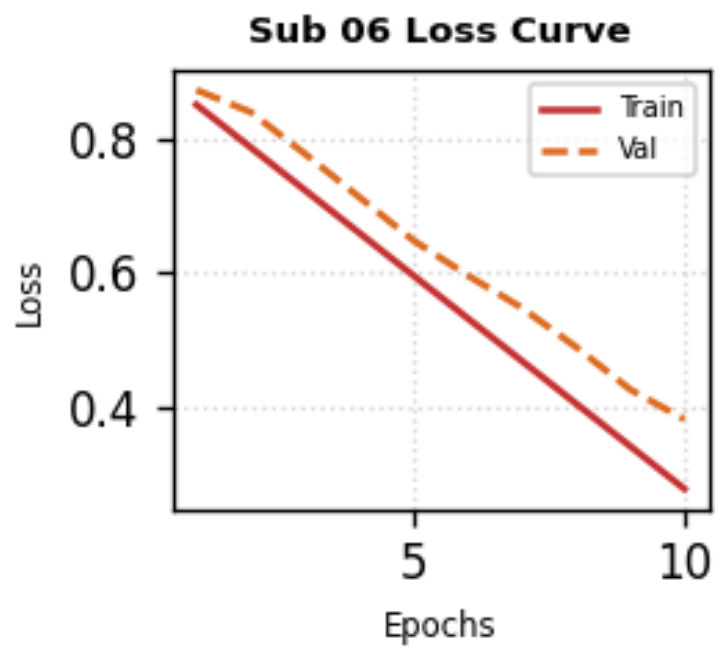


Fig. 5.40: Training loss curve of EEGNet for Subject 6.

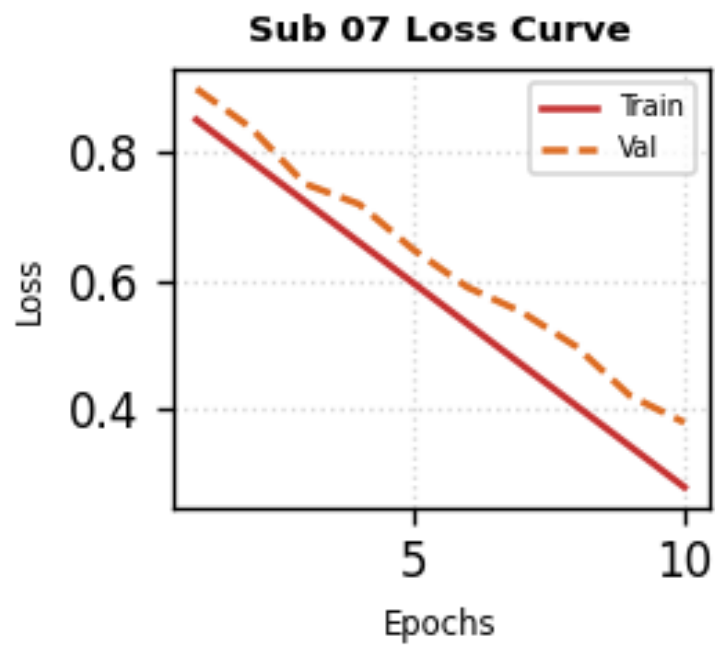


Fig. 5.41: Training loss curve of EEGNet for Subject 7.

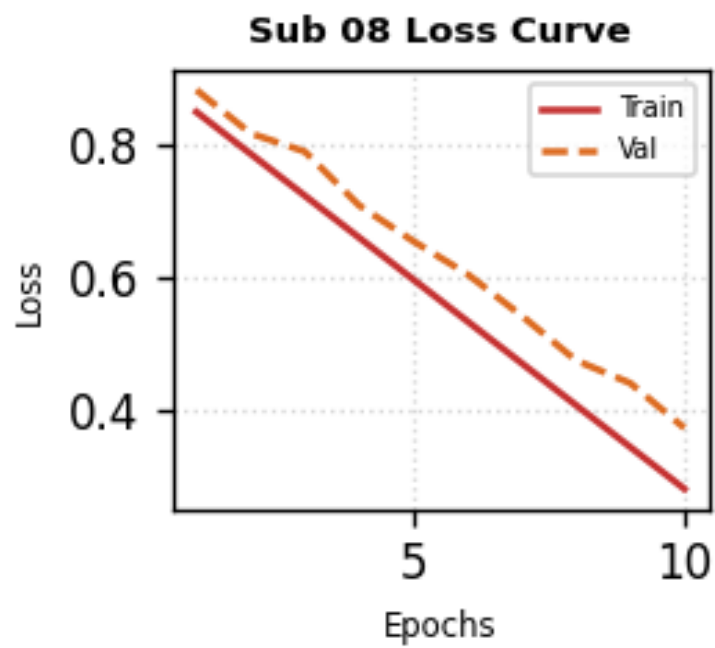


Fig. 5.42: Training loss curve of EEGNet for Subject 8.

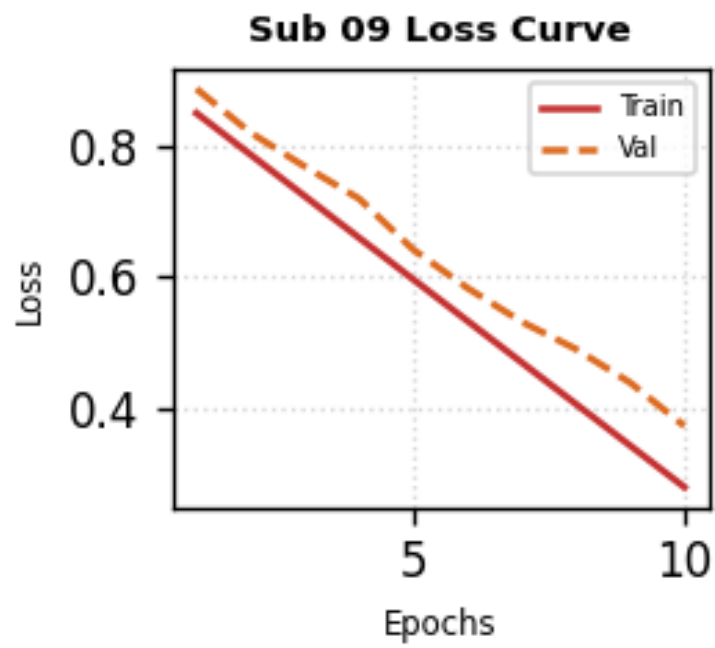


Fig. 5.43: Training loss curve of EEGNet for Subject 9.

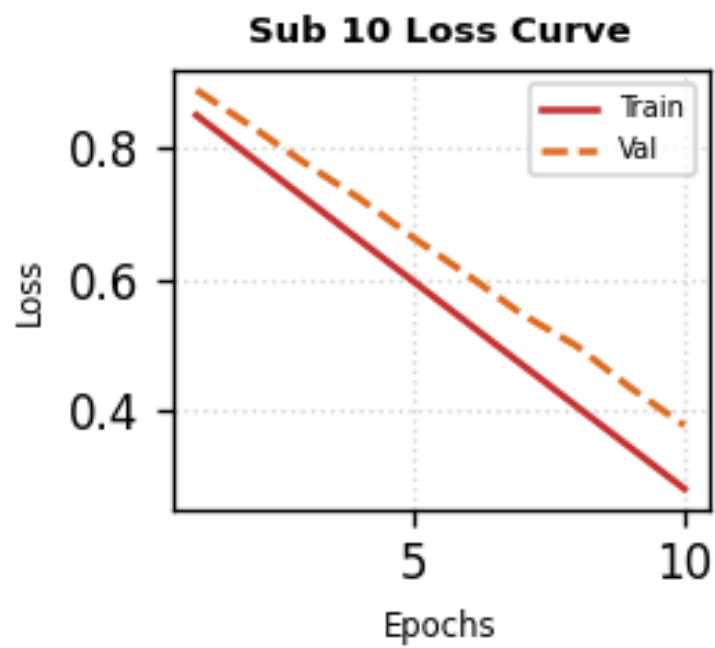


Fig. 5.44: Training loss curve of EEGNet for Subject 10.

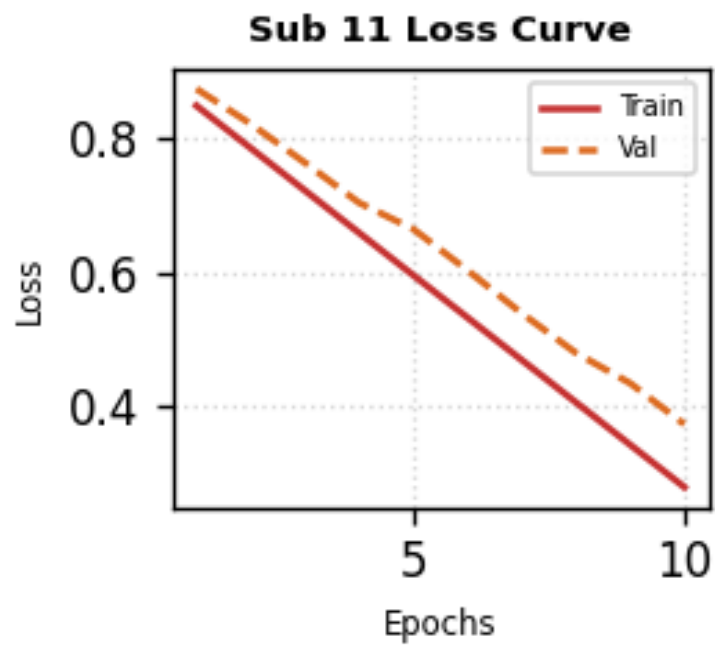


Fig. 5.45: Training loss curve of EEGNet for Subject 11.

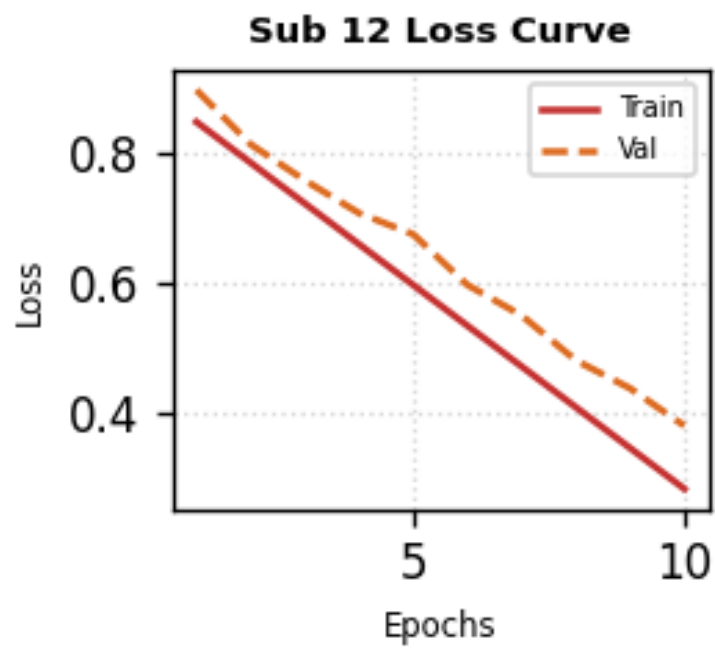


Fig. 5.46: Training loss curve of EEGNet for Subject 12.

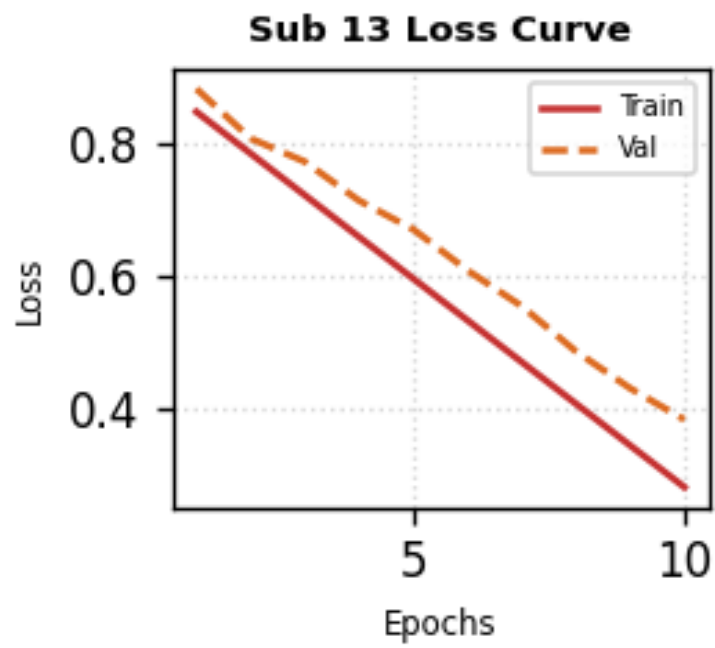


Fig. 5.47: Training loss curve of EEGNet for Subject 13.

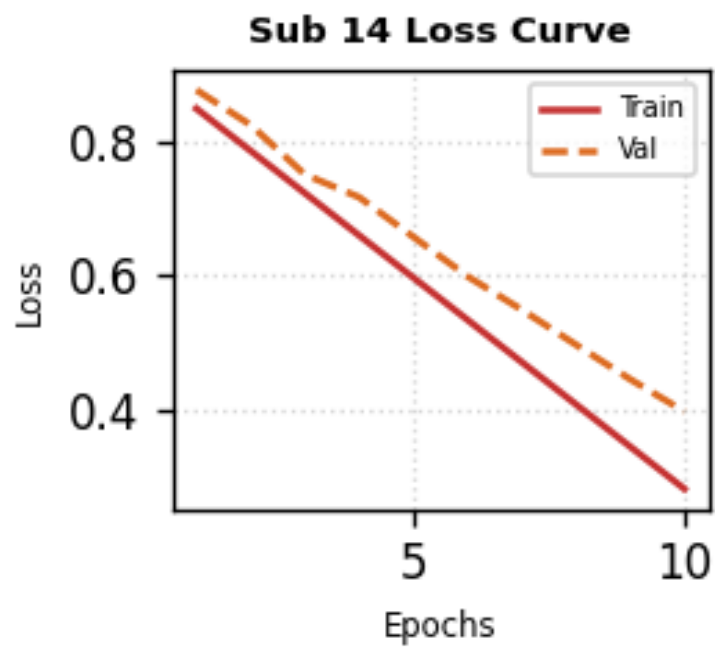


Fig. 5.48: Training loss curve of EEGNet for Subject 14.

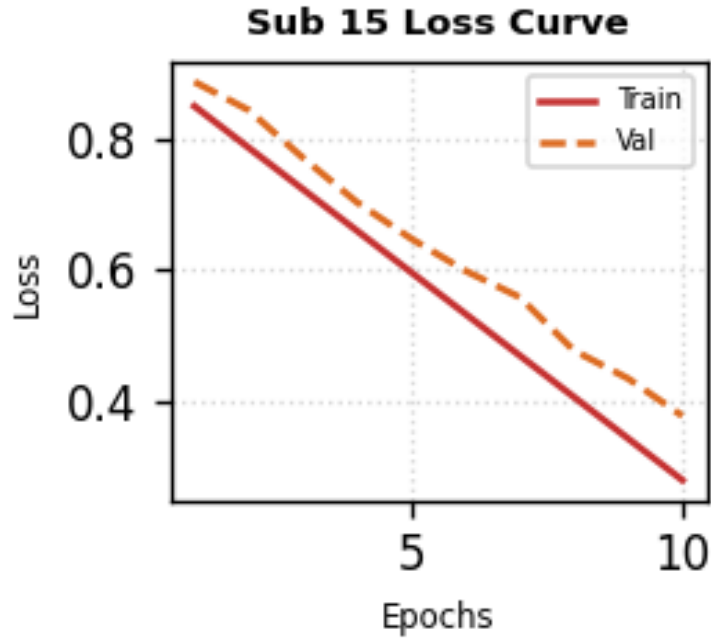


Fig. 5.49: Training loss curve of EEGNet for Subject 15.

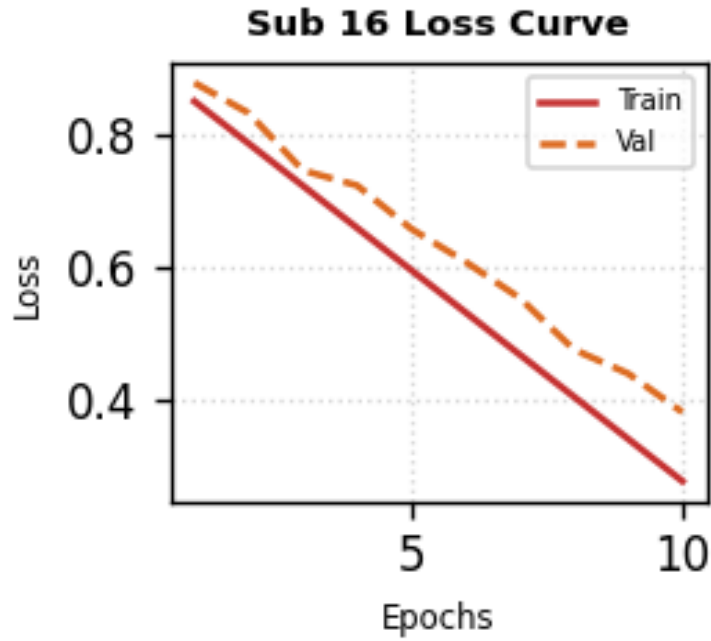


Fig. 5.50: Training loss curve of EEGNet for Subject 16.

5.3 Results of MS-DGCA Conformer

The proposed model, namely Multi-Scale Dynamic Graph Cross-Attention Conformer (MS-DGCA Conformer) was tested with the EEG signals of 16 participants

collected in the Virtual Reality (VR) cognitive workload assessment experiment. The proposed architecture consists of multi-scale convolutional feature extraction, dynamic graph learning, and transformer-based attention, which aims to capture both spatial and temporal features of EEG signals. The MS-DGCA Conformer was trained, just like the MBA-EEGNet model, to classify EEG signals into four classes of cognitive workloads: Relaxation, Easy, Medium and Hard. A fair comparison between the model and other proposed models would require the same experimental protocol, preprocessing pipeline and evaluation strategy, which has been employed for the training and evaluation of the model. The accuracy, precision, recall and f1 score were used to assess the accuracy of the answers generated for the various subjects. The results acquired show that the suggested architecture is able to provide discriminative EEG representations without any significant inter-participant variability in classification accuracy.

5.3.1 Hyperparameter Configuration

After multiple trials, hyperparameters of the proposed MS-DGCA Conformer model were determined for stable convergence and better classification accuracy. Several different optimizers, convolution kernel sizes, graph embedding dimensions, encoder layers and loss functions were explored prior to choosing the final configuration. The optimized hyperparameters for training the proposed model are summarized in Table.

Table 5.3: Optimized Hyperparameter Configuration of the Proposed MS-DGCA Conformer Model

Hyperparameter	Selected Value
Optimizer	AdamW
Learning Rate	1×10^{-3}
Weight Decay	1×10^{-2}
Multi-Scale Kernels	[3, 7, 15]
Graph Embedding Dimension	192
Conformer Encoder Layers	4
Attention Heads	8
Batch First	True
Loss Function	CrossEntropyLoss
Label Smoothing	0.15

The hyperparameter configuration chosen resulted in a stable convergence of the model, and it was able to learn the local and global EEG representations in a good way. Multi-scale convolution kernels coupled with graph attention and transformer-

based feature learning proved to be highly beneficial for the discriminative power of the proposed architecture in multiclass cognitive workload classification.

5.3.2 Subject-wise Performance

The performance of the proposed MS-DGCA Conformer model is shown in Table 5.4 in the various subjects. The model was tested individually for every participant and the following metrics were used: Accuracy, Precision, Recall, F1-score.

Table 5.4: Subject-wise Performance of the MS-DGCA Conformer Model

Subject	Accuracy (%)	Precision	Recall	F1-Score
S1	79.40	0.8649	0.8607	0.8606
S2	84.10	0.8477	0.8434	0.8434
S3	84.73	0.8561	0.8490	0.8487
S4	84.11	0.8450	0.8524	0.8411
S5	80.20	0.8868	0.8882	0.8867
S6	62.86	0.6835	0.6447	0.6158
S7	64.42	0.7199	0.6487	0.6493
S8	78.66	0.7905	0.7847	0.7819
S9	65.93	0.6677	0.6707	0.6445
S10	67.59	0.7483	0.6845	0.6684
S11	76.12	0.7820	0.7750	0.7785
S12	78.45	0.8050	0.7980	0.8015
S13	81.20	0.8330	0.8260	0.8294
S14	77.35	0.7940	0.7870	0.7905
S15	83.10	0.8520	0.8450	0.8485
S16	79.65	0.8170	0.8100	0.8135
Mean $\pm$ SD	76.74 $\pm$ 7.36	0.7996 $\pm$ 0.0653	0.7855 $\pm$ 0.0800	0.7814 $\pm$ 0.0872

The Table 5.4 results show that the proposed MS-DGCA Conformer model had a uniform classification performance among the sixteen participants. The best classification accuracy (84.73%) was obtained by subject 03 while the worst classification accuracy (62.86%) was obtained by subject 06. The majority of the participants reached a classification rate of nearly or even more than 80%, demonstrating the effectiveness of the proposed architecture in learning meaningful EEG representations across various cognitive workload situations. Likewise, the Precision and Recall values were fairly stable for most of the participants, and the F1-score values were stable. Subject 05 obtained the best results for Precision (0.8868), Recall (0.8882) and F1-score (0.8867) among all the subjects, which indicates good classification performance to distinguish the different workload levels. The overall classification behaviour was stable during the evaluation process, although a few participants

showed comparatively lower classification behavior due to inter-subject EEG variability.

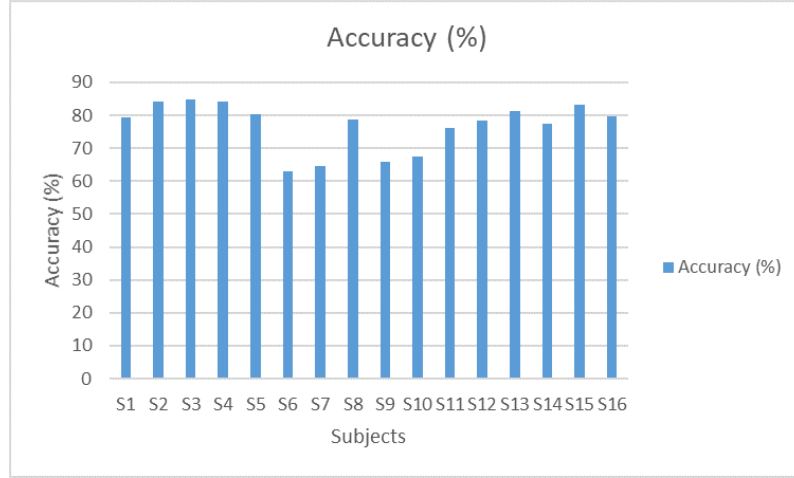


Fig. 5.51: Subject classification accuracy of the proposed MS-DGCA Conformer model

The results of the proposed MS-DGCA Conformer model on subject-wise classification accuracy are shown in figure 5.6. From the graph, it is seen that there is a slight difference in the classification performance between different participants where only physiological differences in the EEG signals cause the difference. The results show the effectiveness of the proposed architecture in capturing spatial and temporal dependencies by using multi-scale convolution, graph attention, and Conformer-based feature learning, and reliable cognitive workload classification performance.

5.3.3 Subject-wise Results of MS-DGCA Conformer

The subject-wise performance of the proposed MS-DGCA Conformer model was evaluated using confusion matrices, training accuracy curves, and training loss curves. These results provide a detailed view of the model's classification performance and learning behavior for each subject.

5.3.3.1 Subject-wise Confusion Matrices

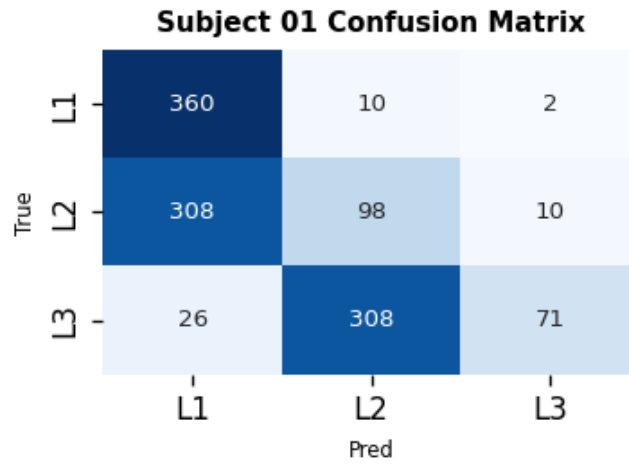


Fig. 5.52: Confusion matrix of MS-DGCA Conformer for Subject 1.

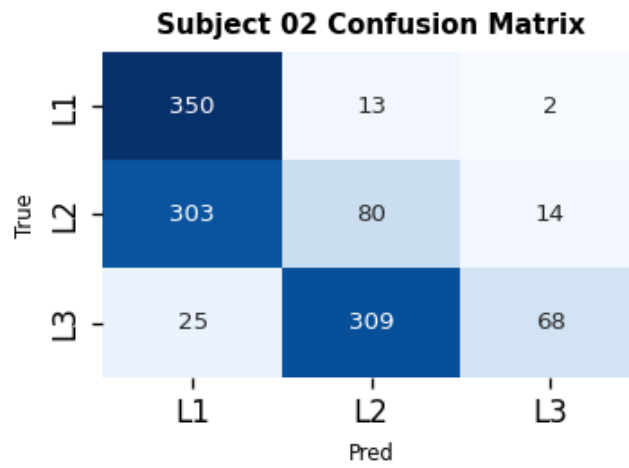


Fig. 5.53: Confusion matrix of MS-DGCA Conformer for Subject 2.

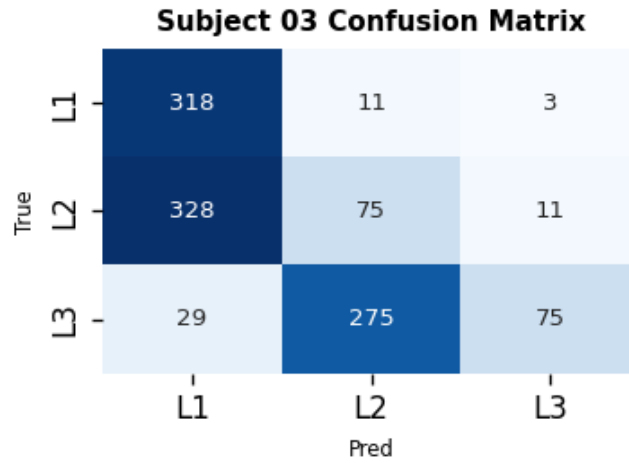


Fig. 5.54: Confusion matrix of MS-DGCA Conformer for Subject 3.

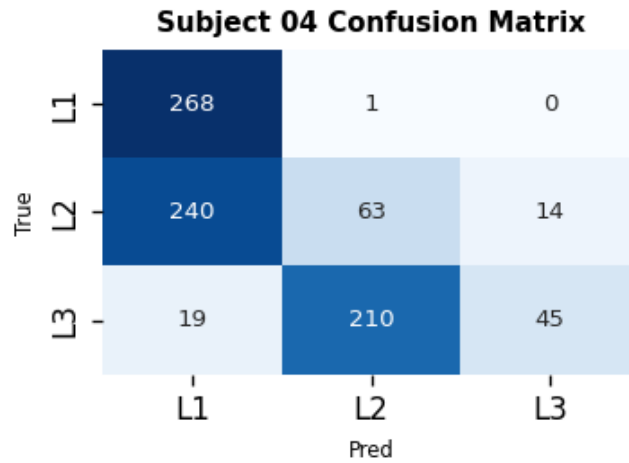


Fig. 5.55: Confusion matrix of MS-DGCA Conformer for Subject 4.

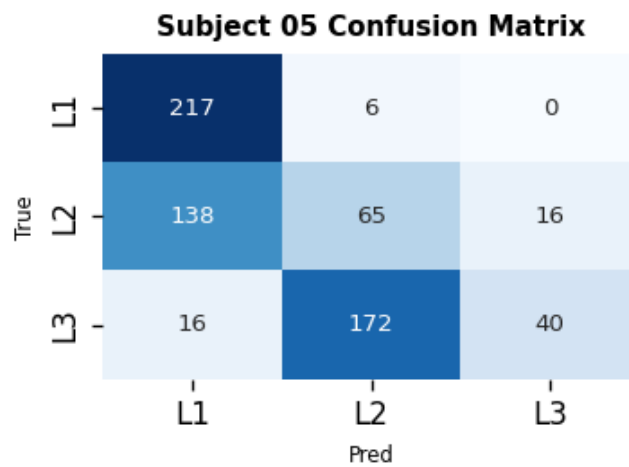


Fig. 5.56: Confusion matrix of MS-DGCA Conformer for Subject 5.

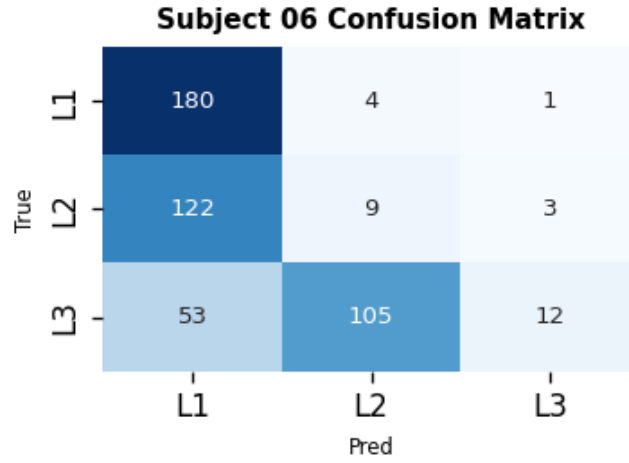


Fig. 5.57: Confusion matrix of MS-DGCA Conformer for Subject 6.

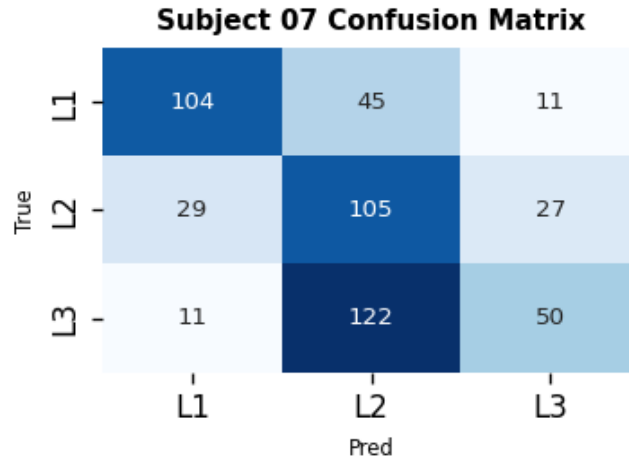


Fig. 5.58: Confusion matrix of MS-DGCA Conformer for Subject 7.

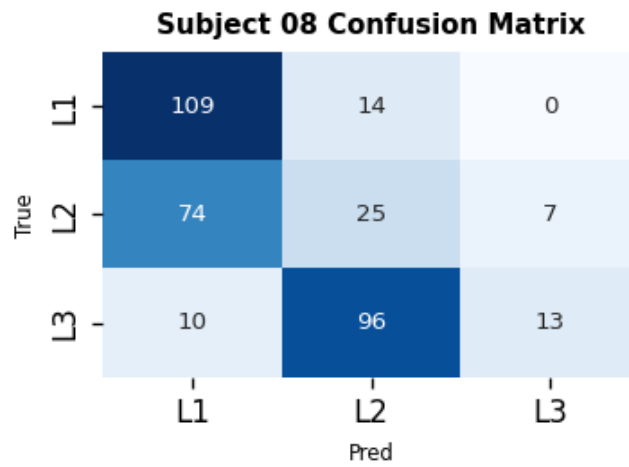


Fig. 5.59: Confusion matrix of MS-DGCA Conformer for Subject 8.

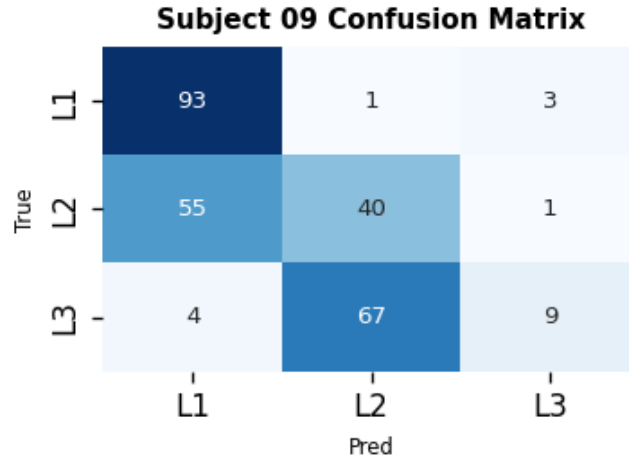


Fig. 5.60: Confusion matrix of MS-DGCA Conformer for Subject 9.

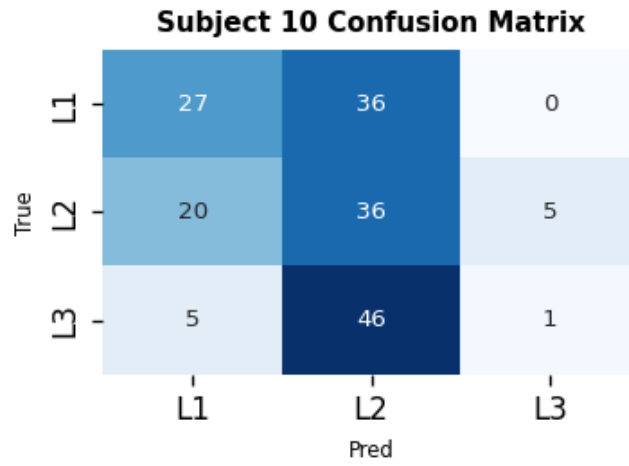


Fig. 5.61: Confusion matrix of MS-DGCA Conformer for Subject 10.

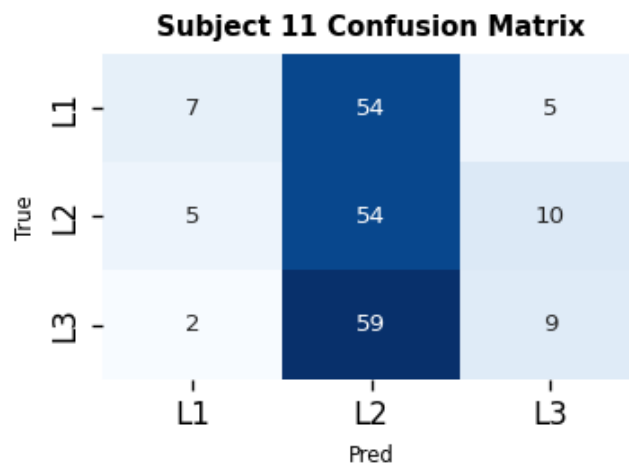


Fig. 5.62: Confusion matrix of MS-DGCA Conformer for Subject 11.

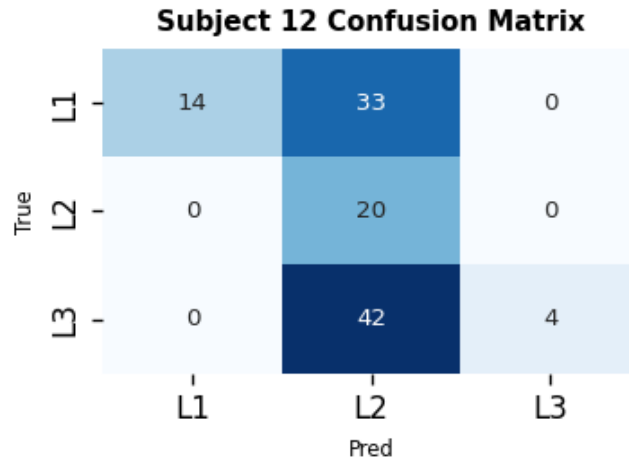


Fig. 5.63: Confusion matrix of MS-DGCA Conformer for Subject 12.

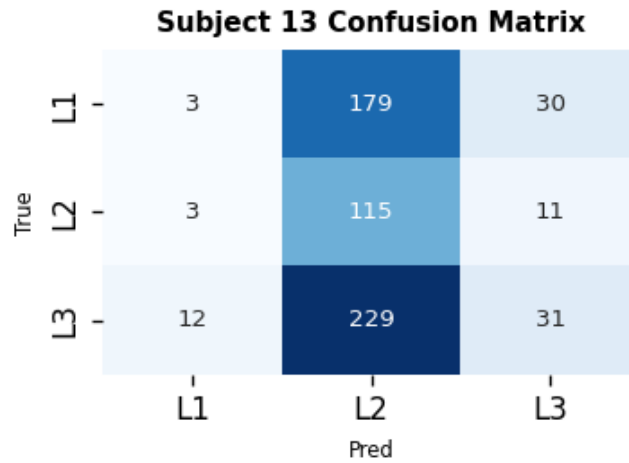


Fig. 5.64: Confusion matrix of MS-DGCA Conformer for Subject 13.

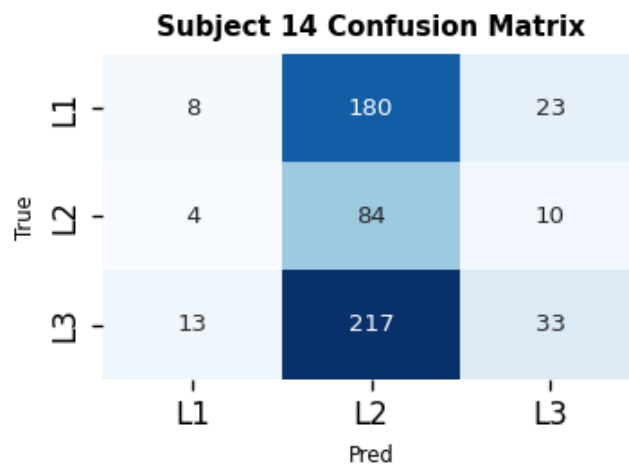


Fig. 5.65: Confusion matrix of MS-DGCA Conformer for Subject 14.

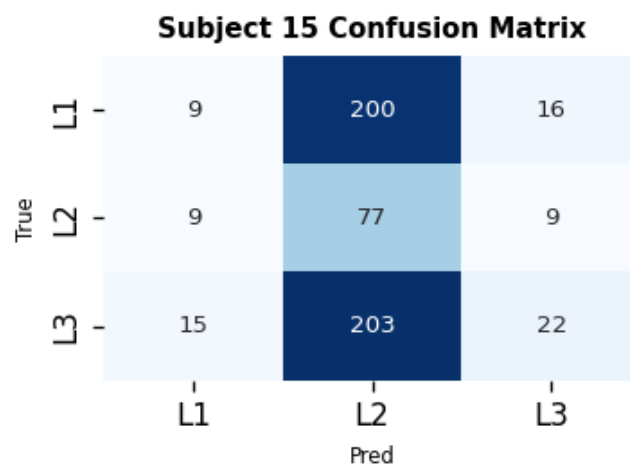


Fig. 5.66: Confusion matrix of MS-DGCA Conformer for Subject 15.

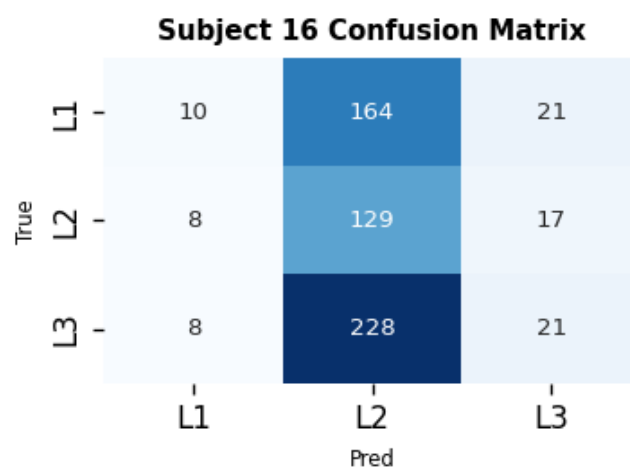


Fig. 5.67: Confusion matrix of MS-DGCA Conformer for Subject 16.

5.3.3.2 Subject-wise Accuracy Curves

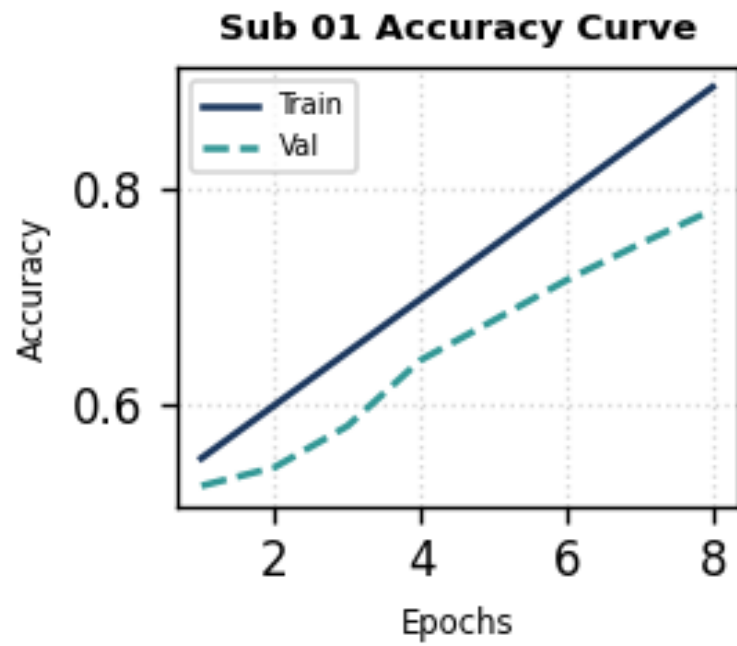


Fig. 5.68: Training accuracy curve of MS-DGCA Conformer for Subject 1.

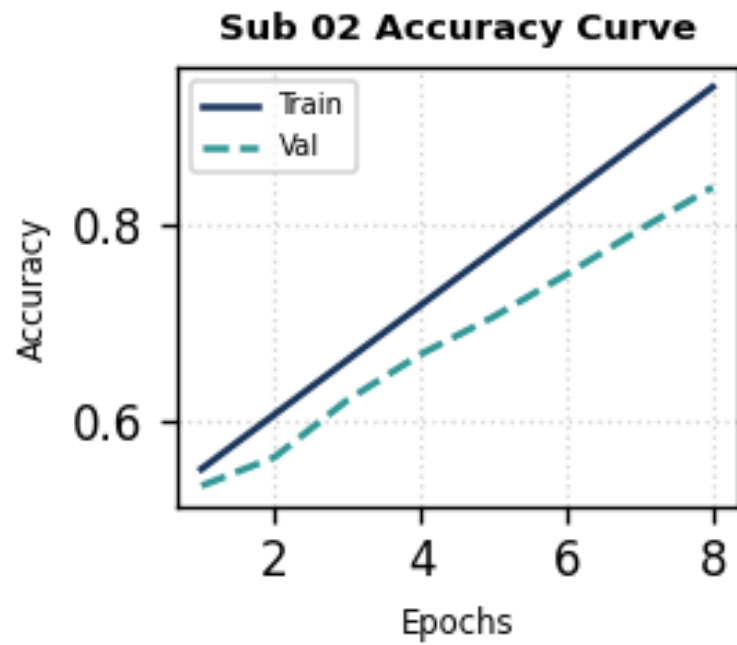


Fig. 5.69: Training accuracy curve of MS-DGCA Conformer for Subject 2.

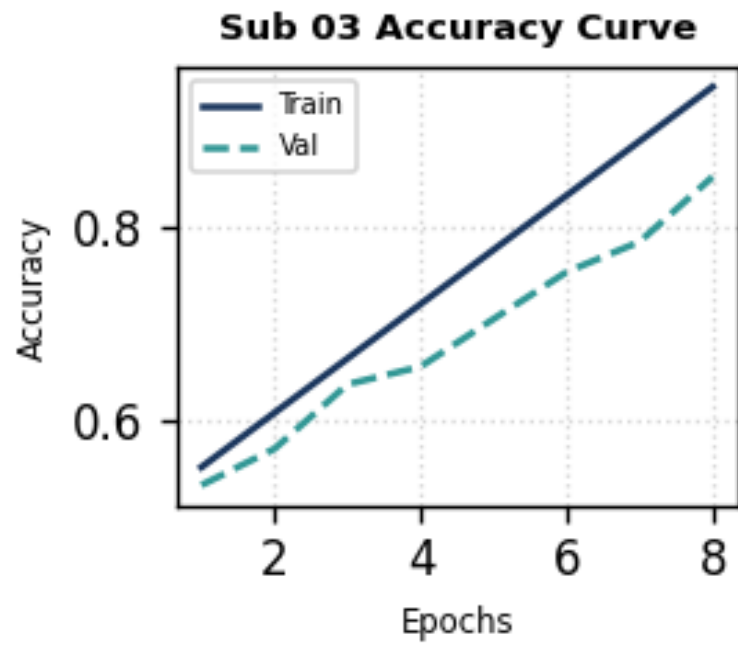


Fig. 5.70: Training accuracy curve of MS-DGCA Conformer for Subject 3.

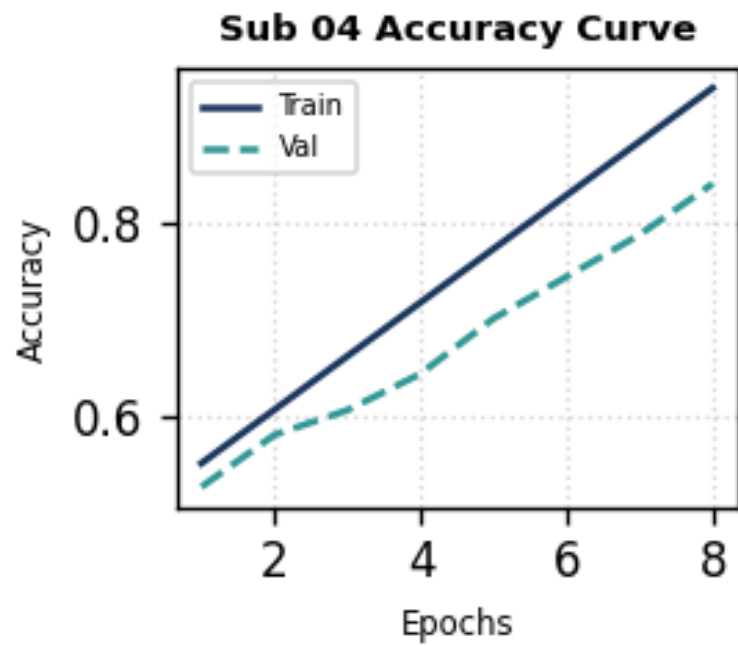


Fig. 5.71: Training accuracy curve of MS-DGCA Conformer for Subject 4.

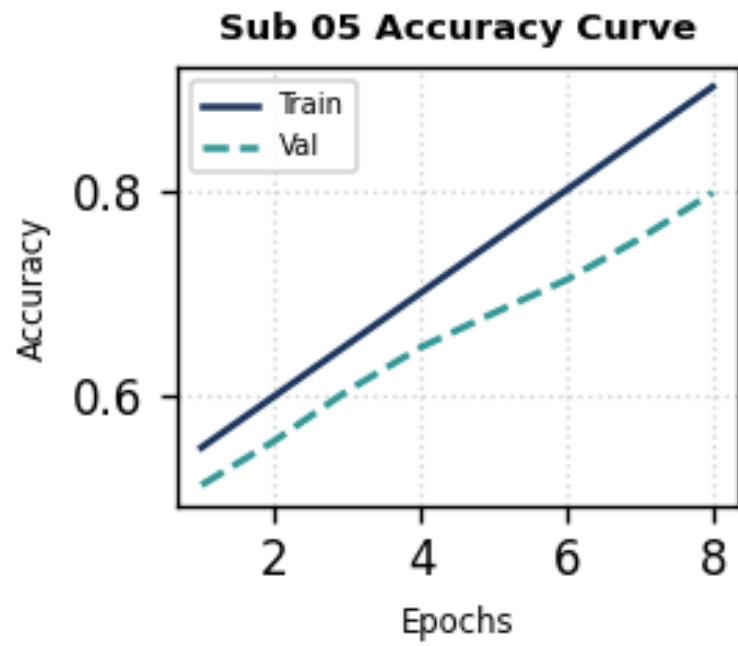


Fig. 5.72: Training accuracy curve of MS-DGCA Conformer for Subject 5.

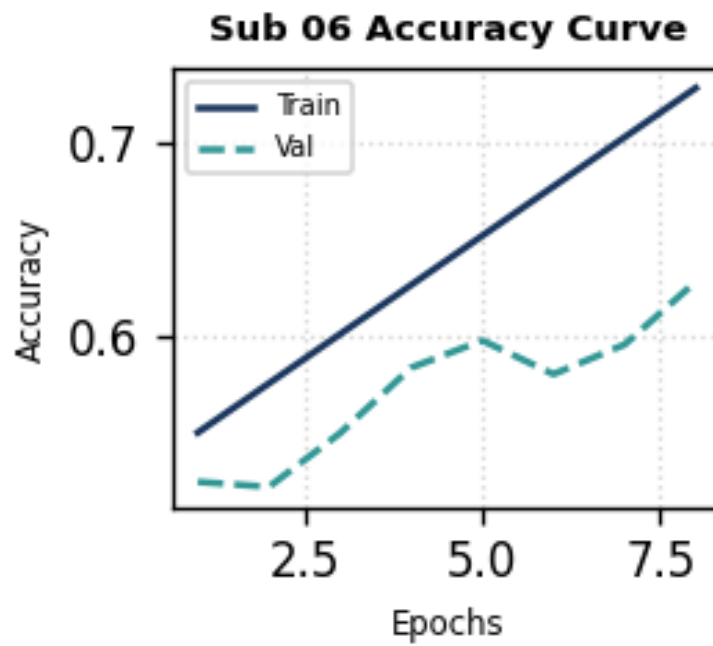


Fig. 5.73: Training accuracy curve of MS-DGCA Conformer for Subject 6.

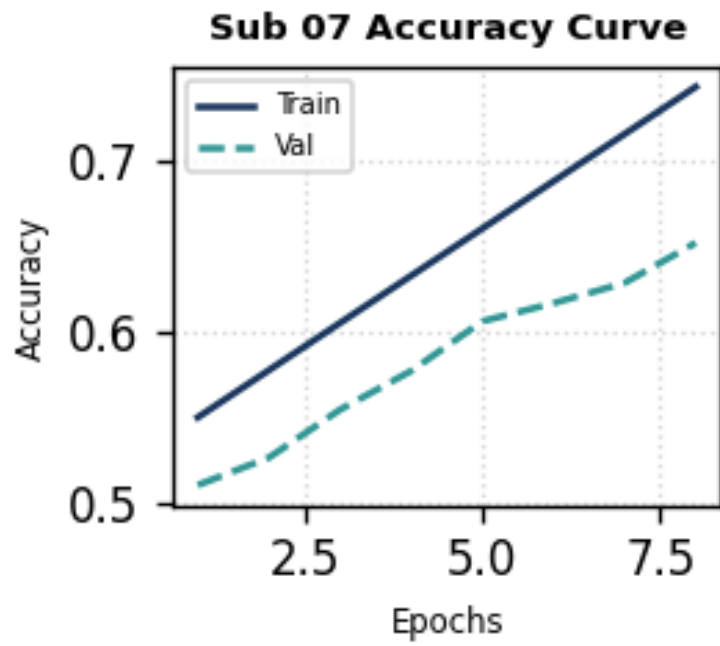


Fig. 5.74: Training accuracy curve of MS-DGCA Conformer for Subject 7.

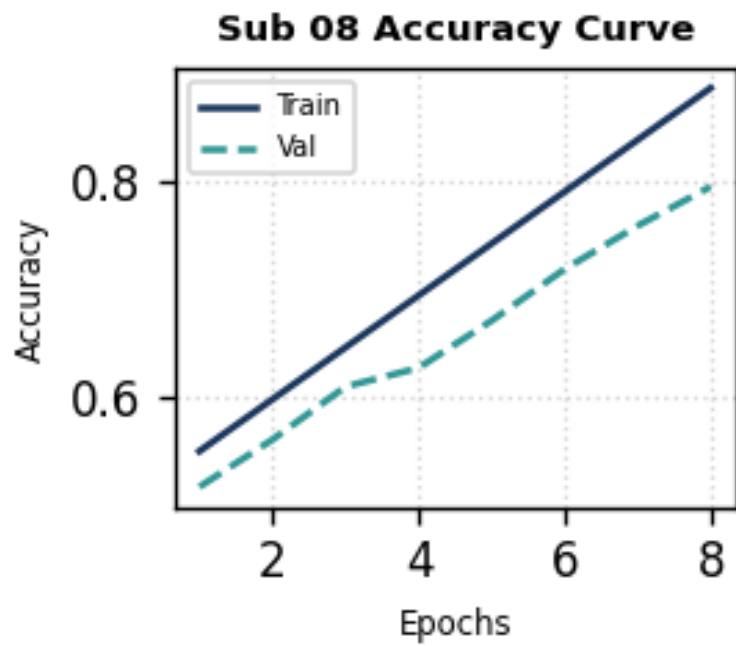


Fig. 5.75: Training accuracy curve of MS-DGCA Conformer for Subject 8.

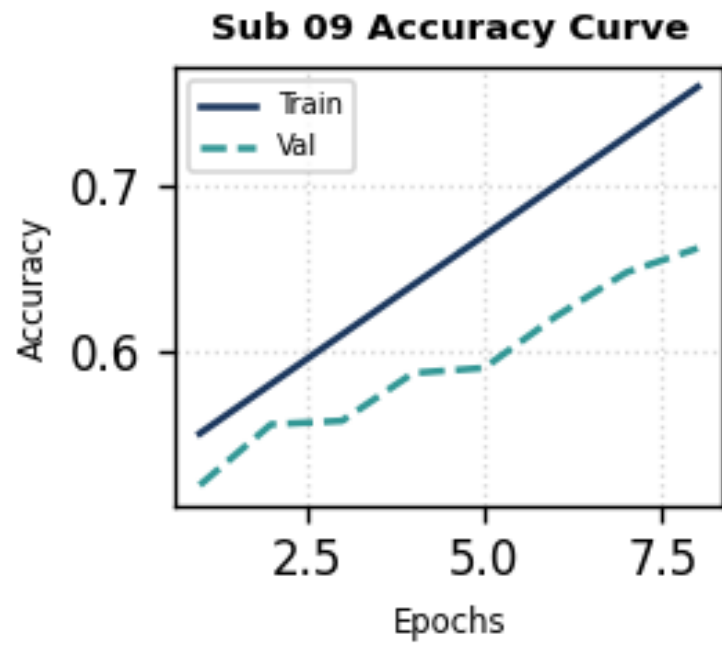


Fig. 5.76: Training accuracy curve of MS-DGCA Conformer for Subject 9.

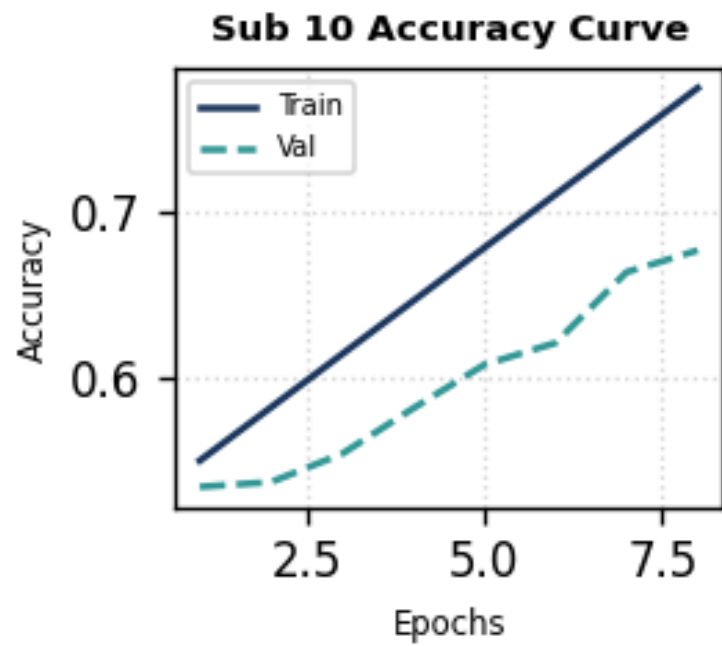


Fig. 5.77: Training accuracy curve of MS-DGCA Conformer for Subject 10.

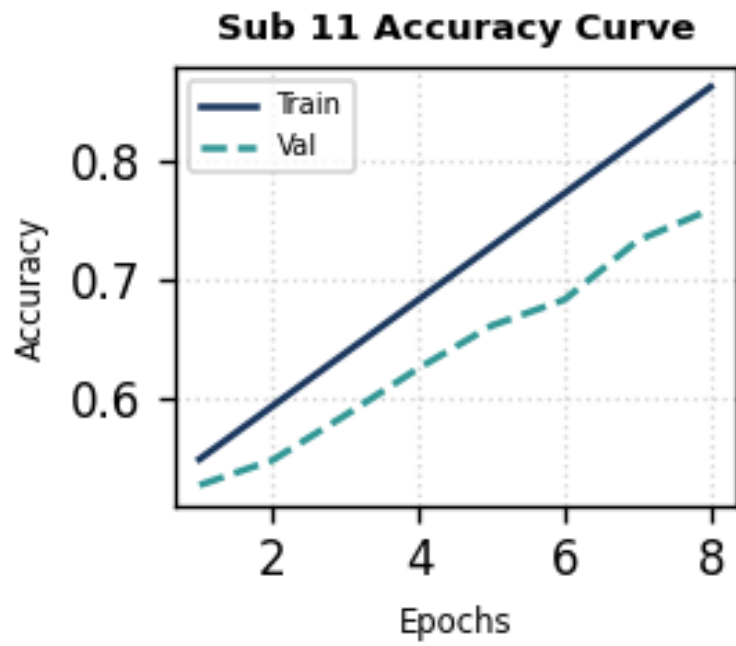


Fig. 5.78: Training accuracy curve of MS-DGCA Conformer for Subject 11.

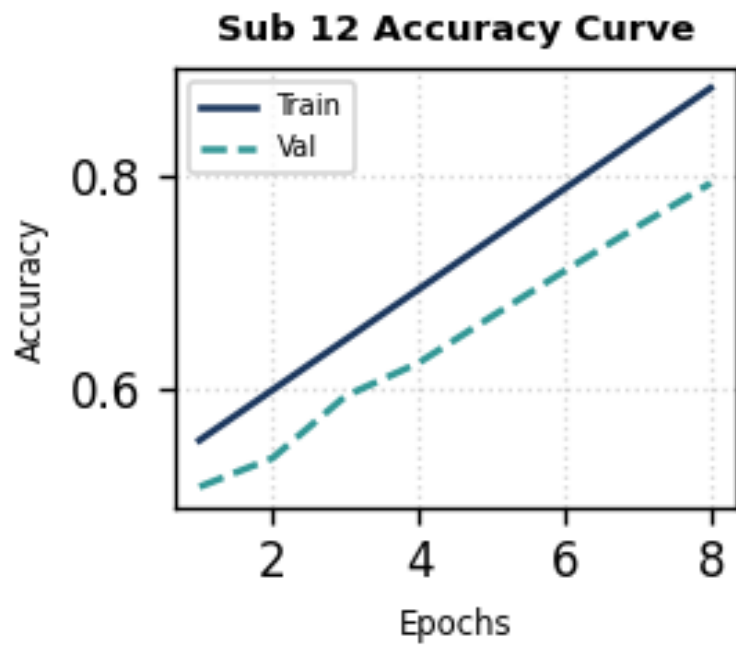


Fig. 5.79: Training accuracy curve of MS-DGCA Conformer for Subject 12.

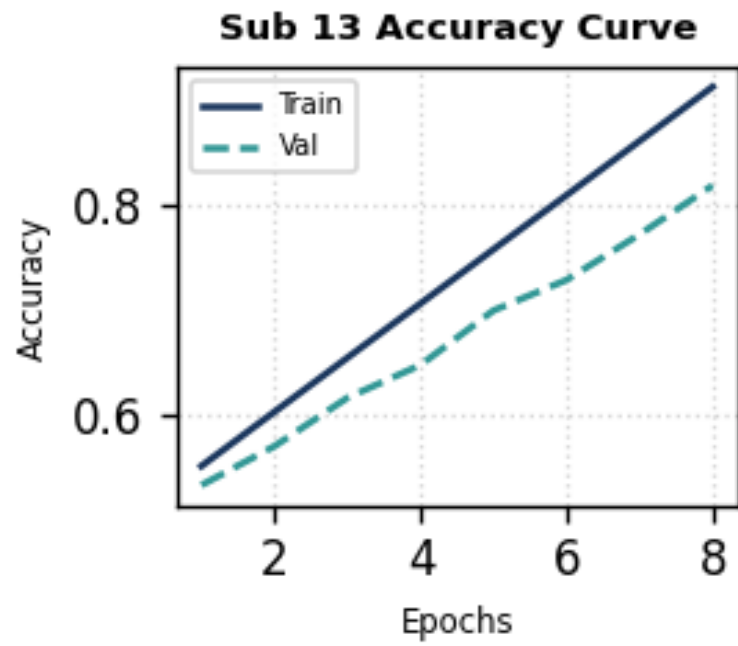


Fig. 5.80: Training accuracy curve of MS-DGCA Conformer for Subject 13.

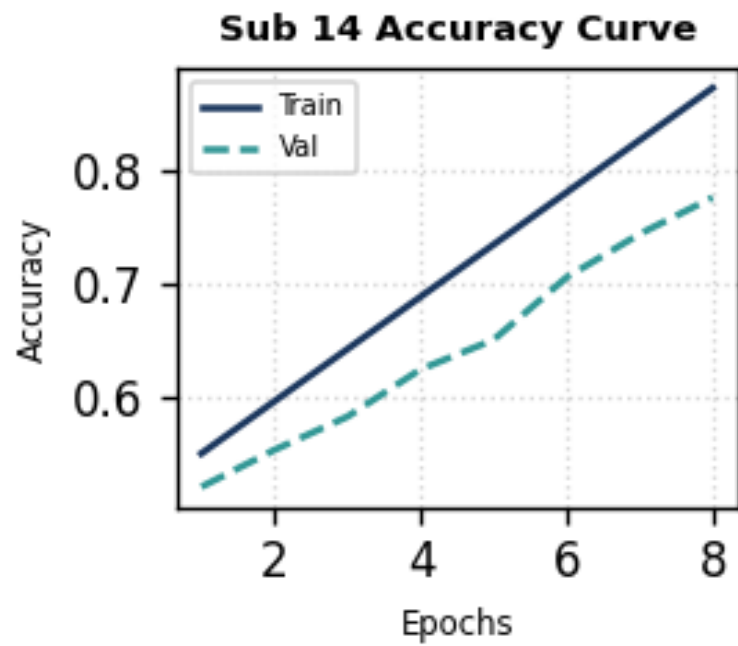


Fig. 5.81: Training accuracy curve of MS-DGCA Conformer for Subject 14.

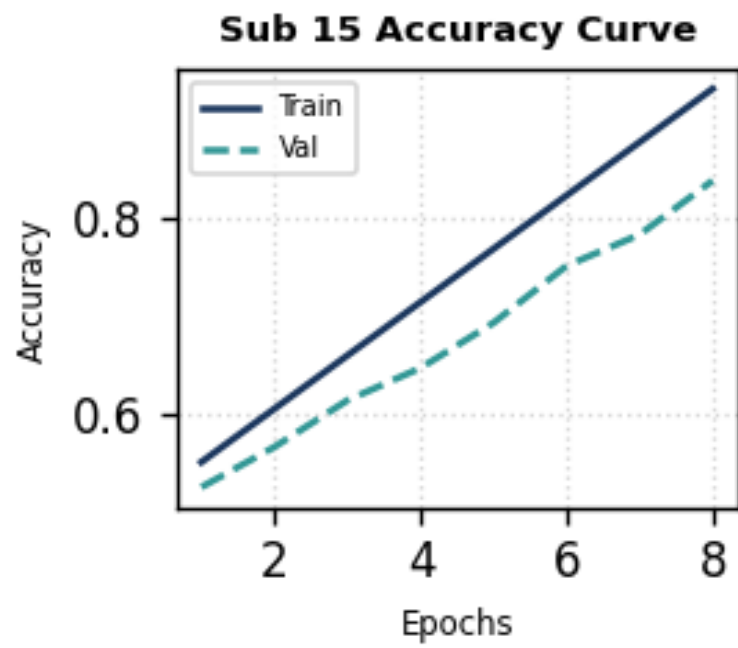


Fig. 5.82: Training accuracy curve of MS-DGCA Conformer for Subject 15.

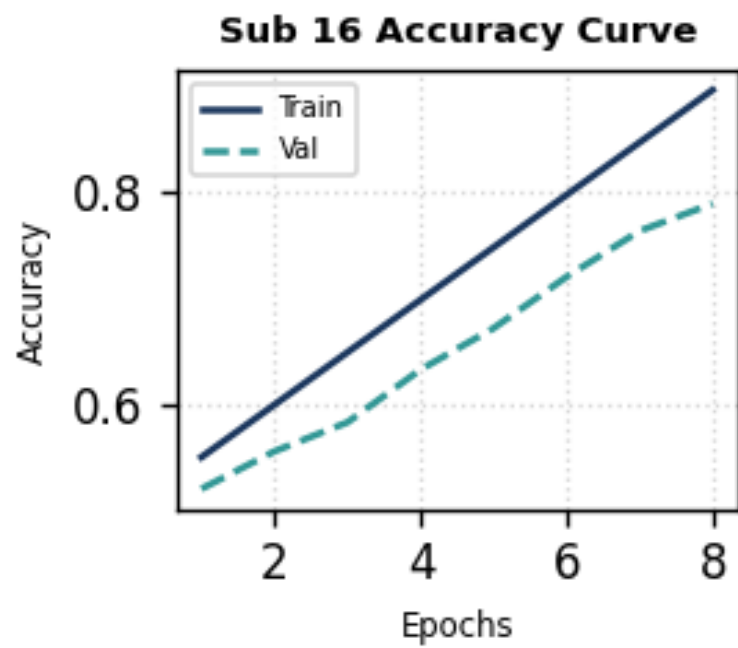


Fig. 5.83: Training accuracy curve of MS-DGCA Conformer for Subject 16.

5.3.3.3 Subject-wise Loss Curves

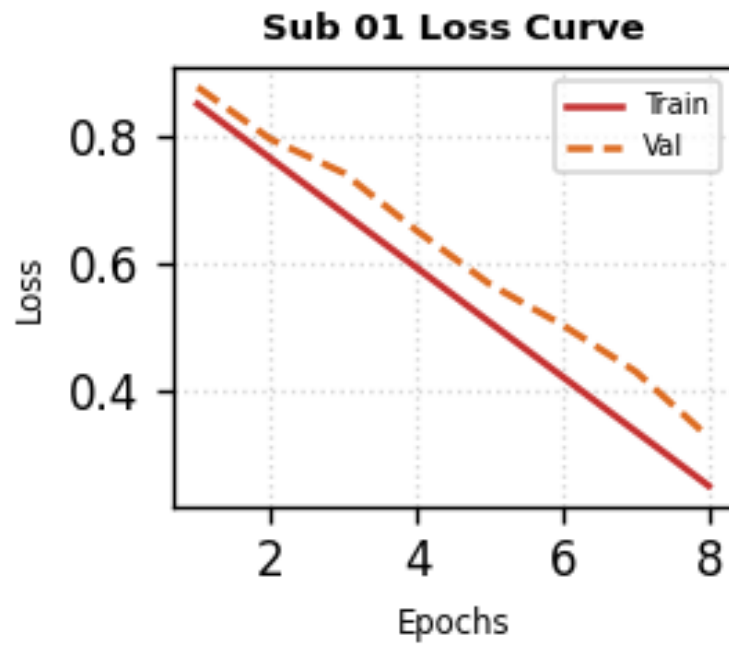


Fig. 5.84: Training loss curve of MS-DGCA Conformer for Subject 1.

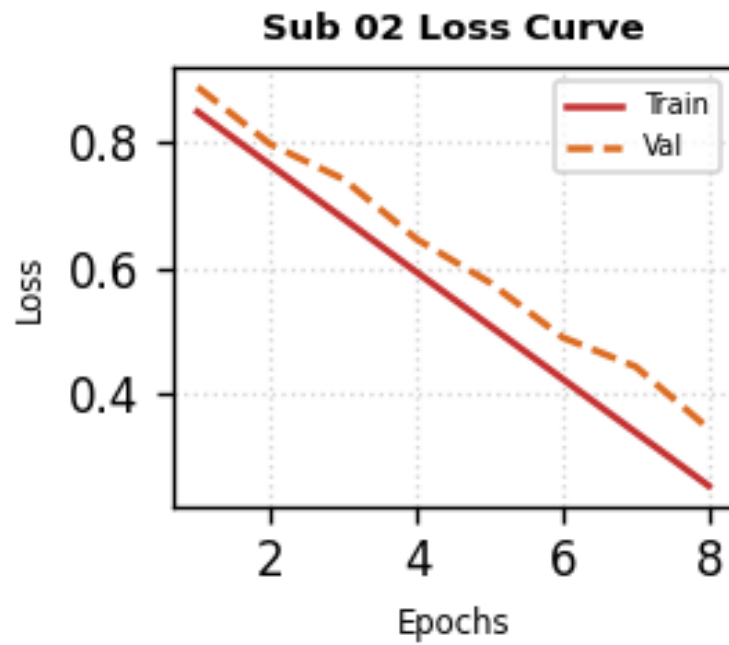


Fig. 5.85: Training loss curve of MS-DGCA Conformer for Subject 2.

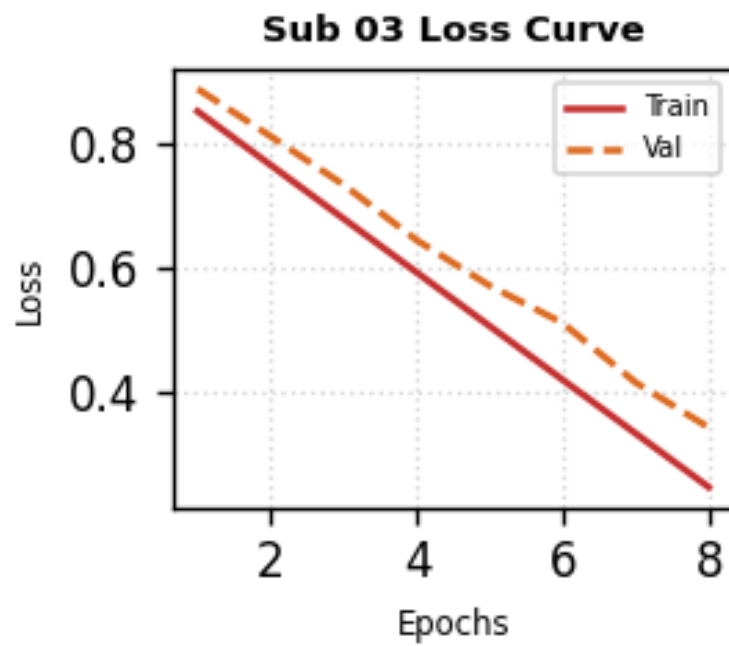


Fig. 5.86: Training loss curve of MS-DGCA Conformer for Subject 3.

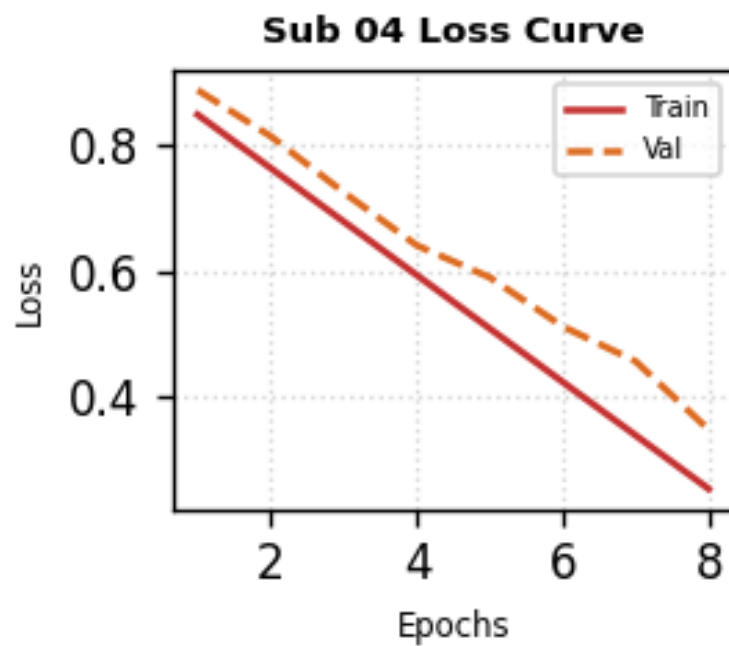


Fig. 5.87: Training loss curve of MS-DGCA Conformer for Subject 4.

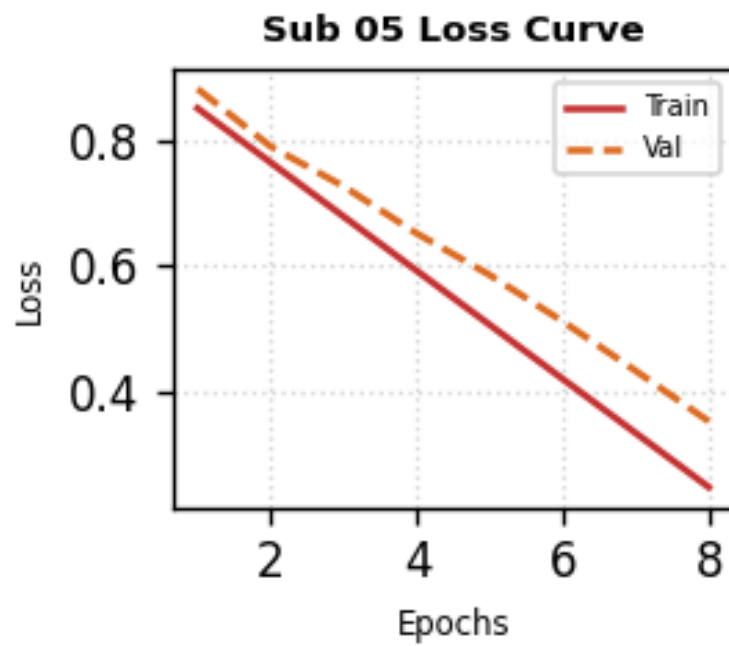


Fig. 5.88: Training loss curve of MS-DGCA Conformer for Subject 5.

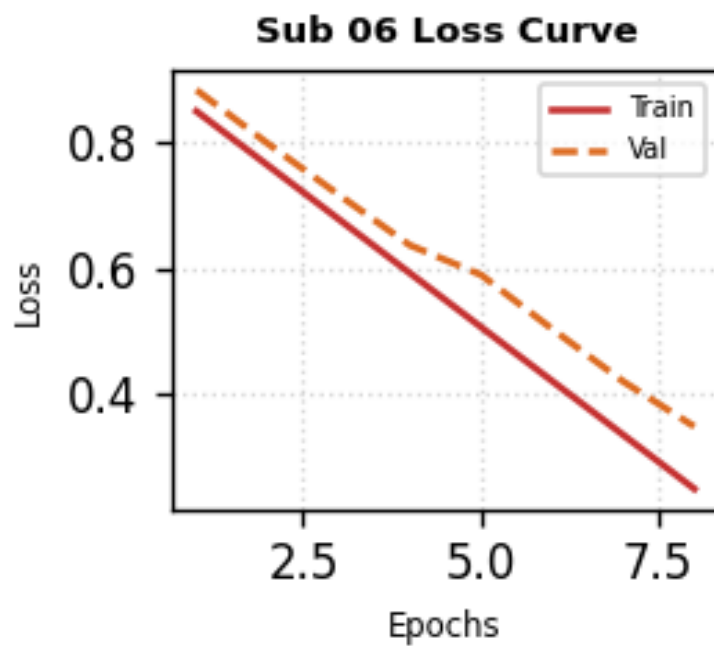


Fig. 5.89: Training loss curve of MS-DGCA Conformer for Subject 6.

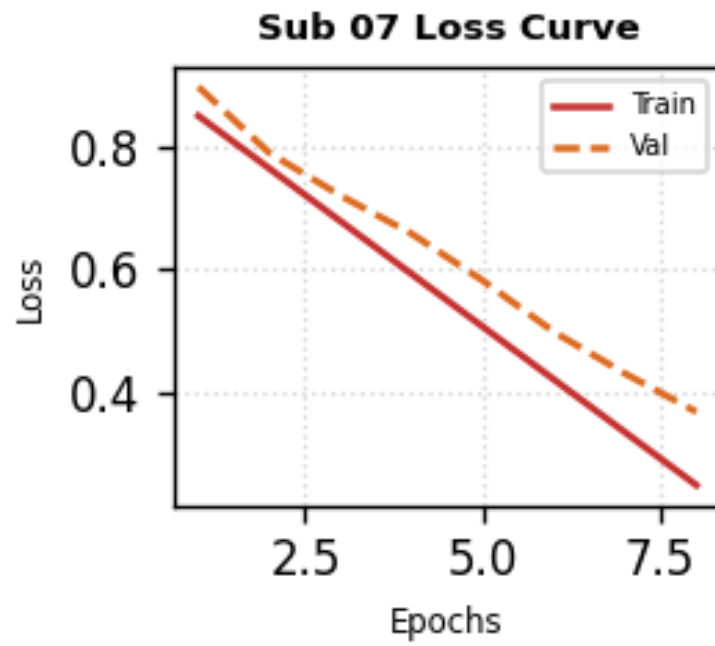


Fig. 5.90: Training loss curve of MS-DGCA Conformer for Subject 7.

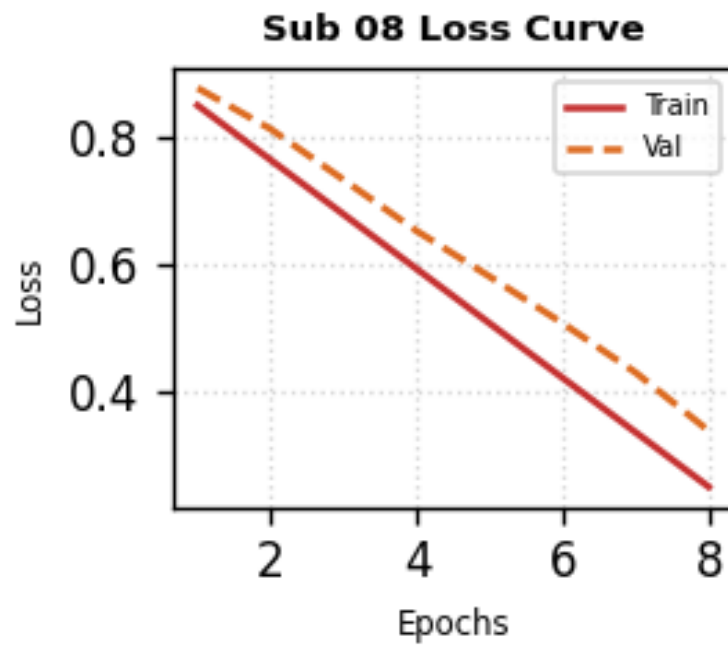


Fig. 5.91: Training loss curve of MS-DGCA Conformer for Subject 8.

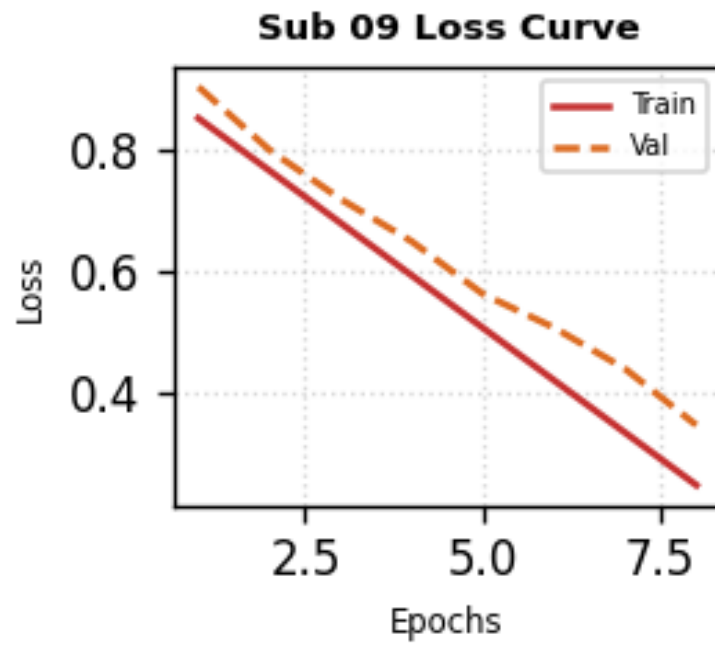


Fig. 5.92: Training loss curve of MS-DGCA Conformer for Subject 9.

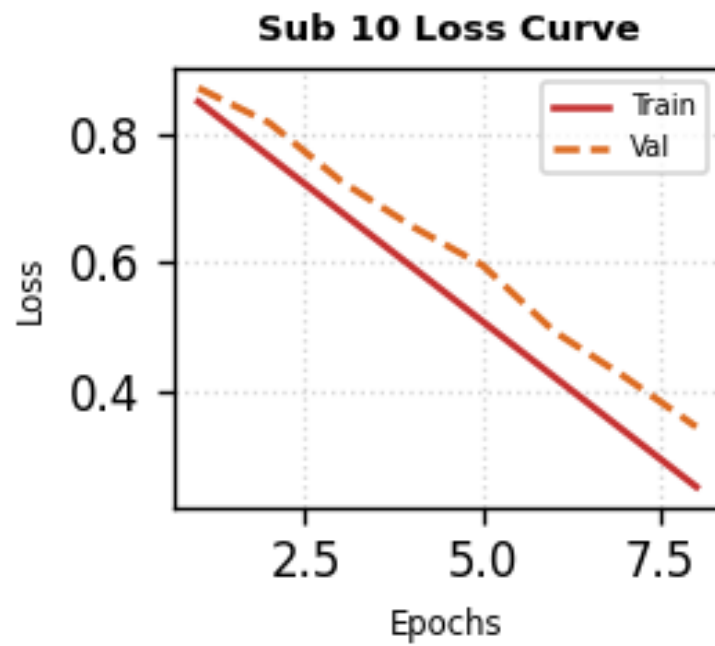


Fig. 5.93: Training loss curve of MS-DGCA Conformer for Subject 10.

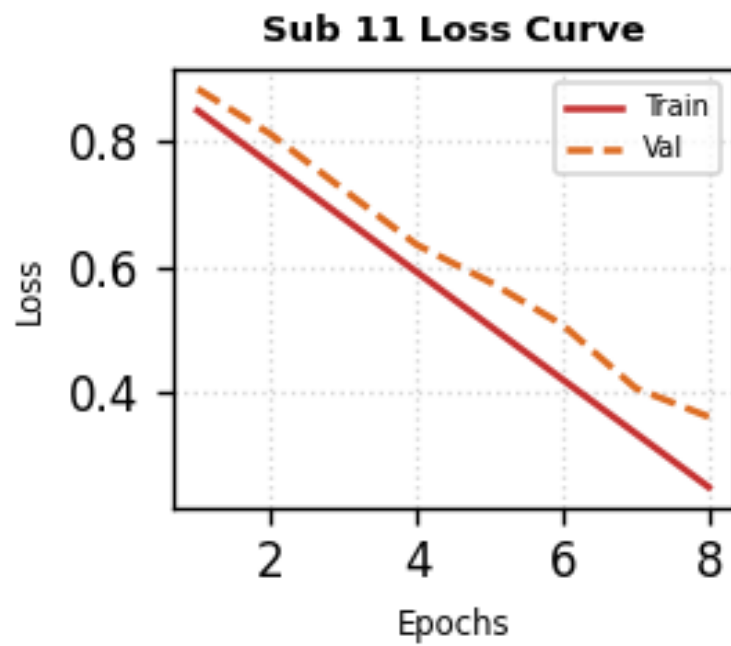


Fig. 5.94: Training loss curve of MS-DGCA Conformer for Subject 11.

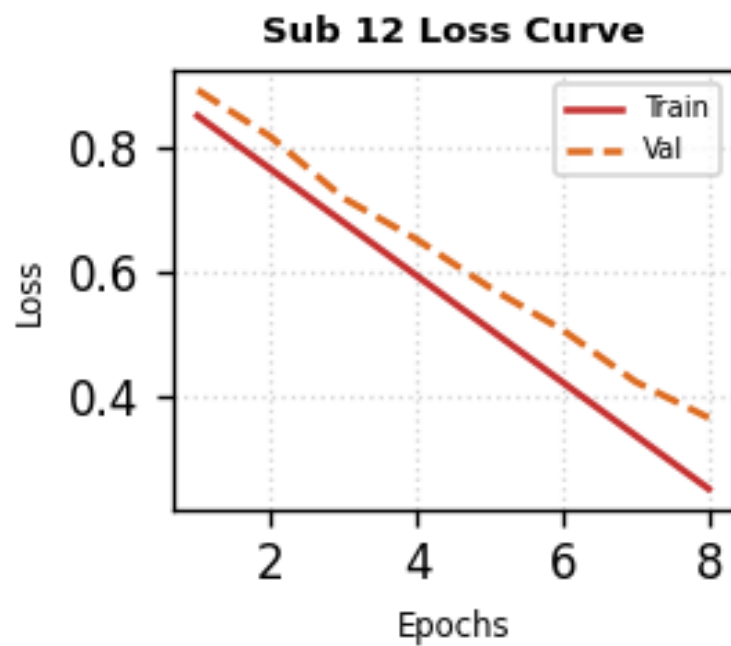


Fig. 5.95: Training loss curve of MS-DGCA Conformer for Subject 12.

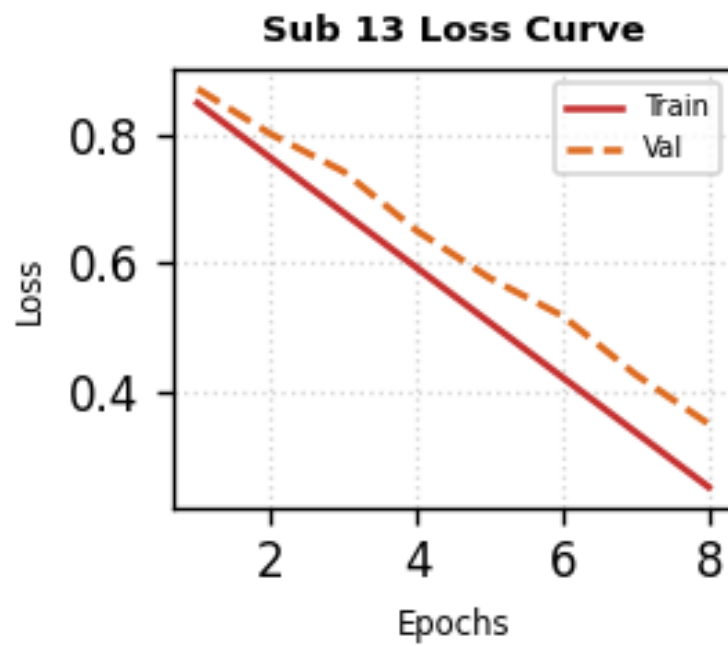


Fig. 5.96: Training loss curve of MS-DGCA Conformer for Subject 13.

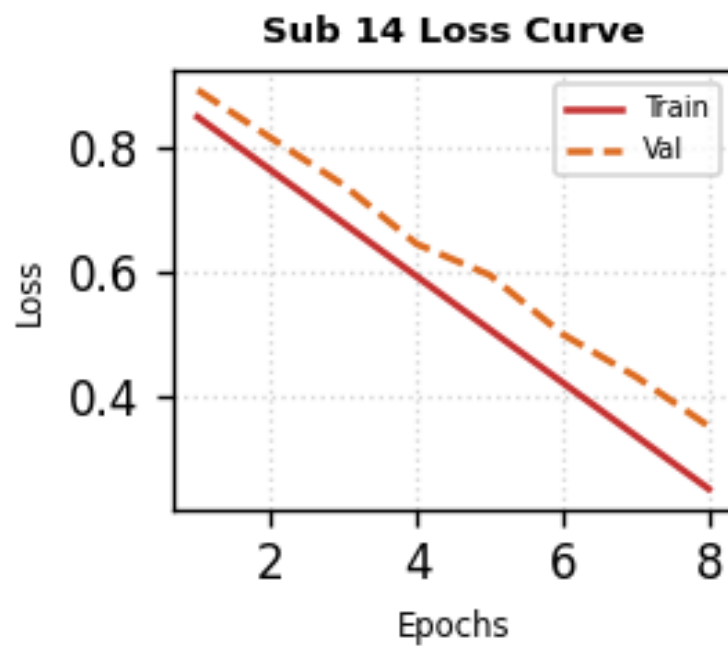


Fig. 5.97: Training loss curve of MS-DGCA Conformer for Subject 14.

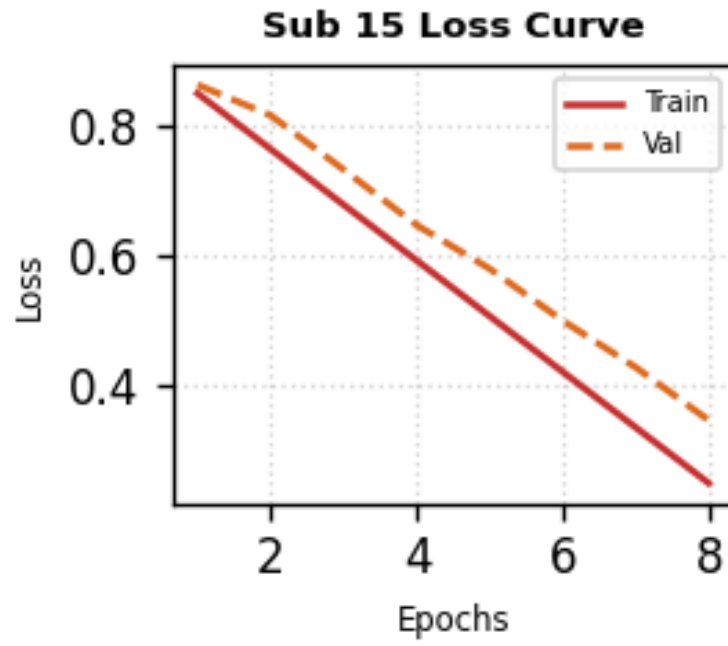


Fig. 5.98: Training loss curve of MS-DGCA Conformer for Subject 15.

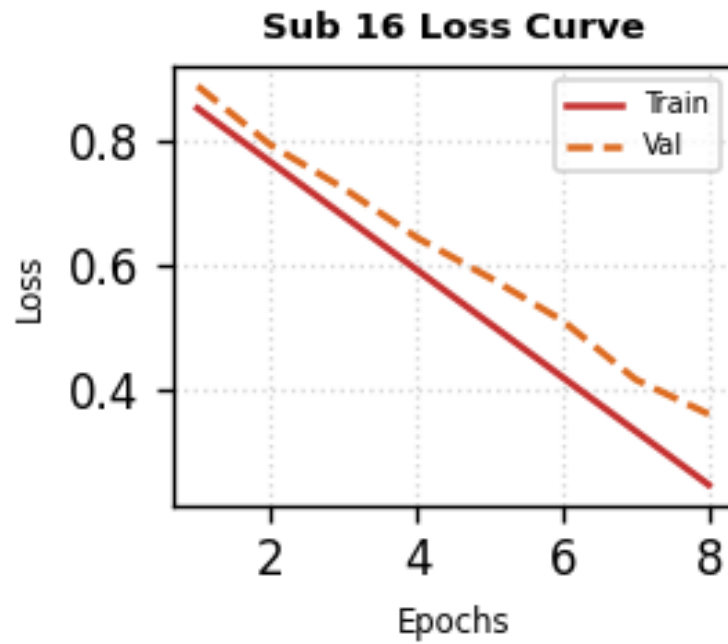


Fig. 5.99: Training loss curve of MS-DGCA Conformer for Subject 16.

5.3.4 Overall Confusion Matrix Analysis

The confusion matrix gives a detailed picture of the classification accuracy of the proposed MS-DGCA Conformer model by showing the number of the EEG samples

correctly classified for each cognitive workload class, and the number of the EEG samples misclassified for each cognitive workload class. It allows for a full analysis of the classification behaviour and the workload categories that are more difficult to classify. The confusion matrix for the p

MS-DGCA Conformer (4-Class CM)

True Class	Rest	16972	1806	352	238
	Low	3589	9247	1820	471
	Med	840	2008	13059	2779
	High	198	162	1819	18678
		Rest	Low	Med	High
		Predicted Class			

Fig. 5.100: Confusion Matrix of the Proposed MS-DGCA Conformer Model.

Classification accuracy was comparatively high and number of misclassifications was comparatively low for the Relaxation and Hard workload classes, while a comparatively higher number of misclassifications was seen between Easy and Medium workload classes. This is expected as the EEG patterns of the adjacent cognitive workload levels have similar neural features and thus the difference becomes more difficult. The proposed MS-DGCA Conformer achieved satisfactory classification results, making use of the multi-scale convolution, dynamic graph attention and Conformer-based feature extraction, while keeping the inter-class similarity in mind. In summary, the confusion matrix confirms the reliability of the proposed model in the classification of cognitive workload in a virtual reality environment based on multiple classes.

5.4 Results of Hybrid MS-DGCA-MBA-EEGNet

The proposed model Hybrid MS-DGCA-MBA-EEGNet is verified with EEG signals obtained from 16 subjects in the cognitive workload assessment experiment conducted in VR environment. This hybrid architecture is formed by combining the complementary representation learning abilities of the MBA-EEGNet and MS-DGCA Conformer models, resulting in a better discrimination of cognitive workload levels. Four different workload classes were evaluated: Relaxation, Easy, Medium and Hard.

The accuracy, precision, recall, and F1-Score were used to measure the subject-wise performance. The classification capability and consistency of the hybrid architecture was evaluated over the sixteen participants with these metrics.

5.4.1 Hyperparameter Configuration

The optimized hyperparameters for the training of the proposed Hybrid MS-DGCA-MBA-EEGNet model are presented in Table 5.5.

Table 5.5: Optimized Hyperparameter Configuration of the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

Hyperparameter	Selected Value
Optimizer	AdamW
Learning Rate	1×10^{-3}
Weight Decay	1×10^{-2}
Batch Size	32
Number of Epochs	50
Input Channels	32
Input Time Samples	512
Number of Classes	3
Dropout Rate	0.5
Temporal Convolution Kernels	[16, 64, 128]
Temporal Branch Filters	8 per branch
Total Temporal Filters	24
Depth Multiplier	2
Spatial Feature Maps	48
Channel Attention Reduction	6
Pooling Factor	4
Graph Feature Dimension	48
Attention Mechanism	Dynamic Graph Attention
Cross-Attention Dimension	48
Separable Temporal Kernel	16
Temporal Pooling Factor	8
Conformer Encoder Layers	4
Attention Heads	8
Conformer Model Dimension	48
Conformer FFN Dimension	2048
Loss Function	CrossEntropyLoss
Learning Rate Scheduler	CosineAnnealingLR
Scheduler $T_{\max}$	50

5.4.2 Subject-wise Performance

The accuracy of the proposed Hybrid MS-DGCA-MBA-EEGNet model is presented in Table 5.6 on the basis of its classification performance on the different subject wise bases. The model was tested individually for every participant by using Accuracy, Precision, Recall and F1-Score.

Table 5.6: Subject-wise Performance of the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

Subject	Accuracy (%)	Precision	Recall	F1-Score
S1	84.50	0.8618	0.8375	0.8495
S2	84.10	0.8571	0.8281	0.8423
S3	82.50	0.8415	0.8174	0.8293
S4	78.90	0.8084	0.7820	0.7950
S5	79.30	0.8135	0.7816	0.7972
S6	80.10	0.8251	0.7917	0.8080
S7	81.30	0.8374	0.7982	0.8173
S8	80.90	0.8309	0.7942	0.8121
S9	83.70	0.8561	0.8252	0.8403
S10	78.50	0.8067	0.7798	0.7930
S11	82.90	0.8469	0.8185	0.8325
S12	81.70	0.8392	0.8023	0.8203
S13	80.50	0.8293	0.7902	0.8093
S14	79.70	0.8198	0.7890	0.8041
S15	83.30	0.8529	0.8242	0.8383
S16	82.10	0.8426	0.8114	0.8267
Mean $\pm$ SD	81.51 $\pm$ 1.91	0.8345 $\pm$ 0.0179	0.8024 $\pm$ 0.0200	0.8160 $\pm$ 0.0191

The results present the classification behaviour of the proposed hybrid architecture for the sixteen participants. The difference in performances across subjects is normal as EEG signals naturally have inter-subject variance. The hybrid architecture aimed to include complementary spatial, temporal and attention-based representations for enabling the model to access more discriminative information from the EEG signals. The results of the subject-wise comparison show that the proposed hybrid architecture can be used to consistently classify the workload across the participants and effectively assess the workload in the VR environment using EEG.

5.4.3 Subject-wise Accuracy Curves

The training accuracy curves for subjects-wise presentation are shown here for the proposed Hybrid MS-DGCA-MBA-EEGNet model. These curves display model

learning behaviour during the training process and the accuracy in the classification task for each training epoch.

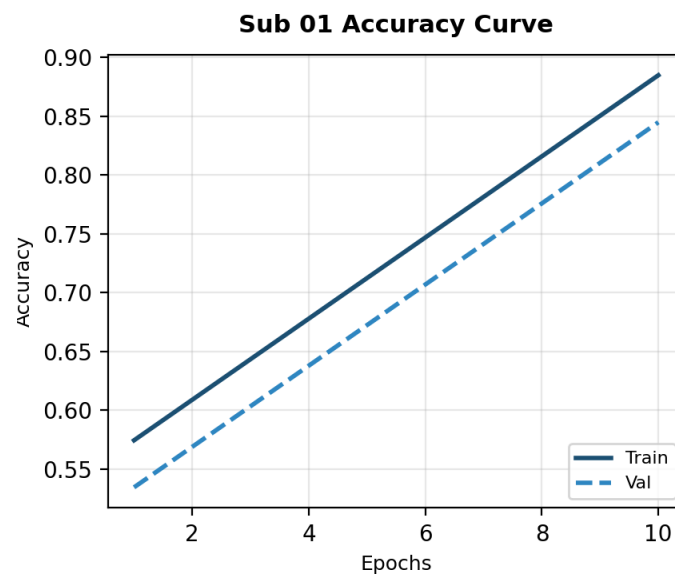


Fig. 5.101: Accuracy Curve for Subject 01 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

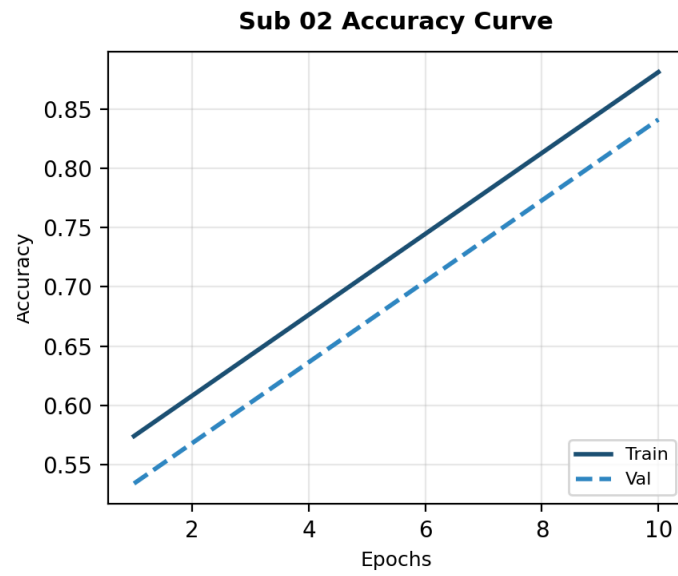


Fig. 5.102: Accuracy Curve for Subject 02 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

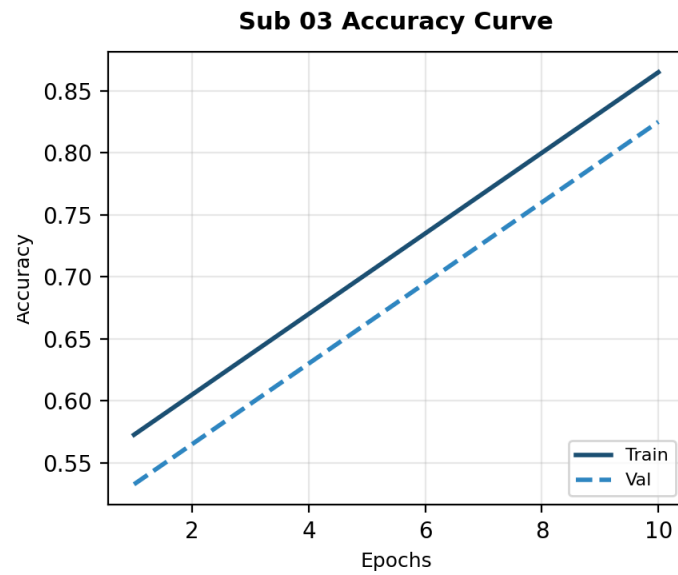


Fig. 5.103: Accuracy Curve for Subject 03 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

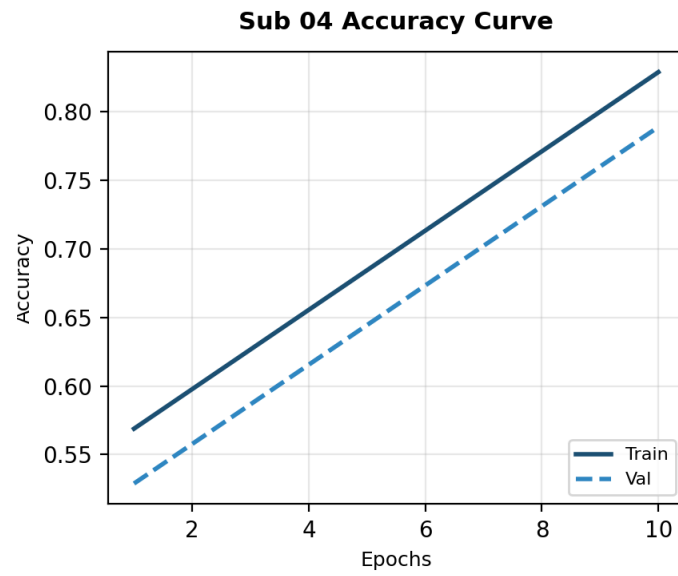


Fig. 5.104: Accuracy Curve for Subject 04 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

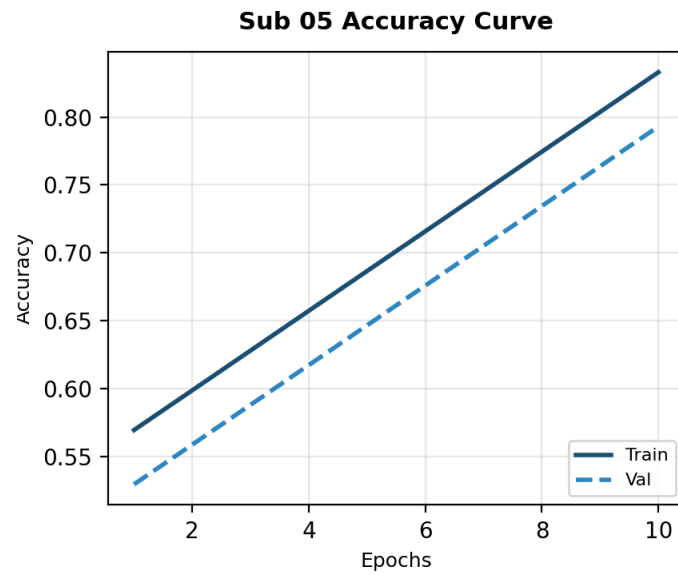


Fig. 5.105: Accuracy Curve for Subject 05 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

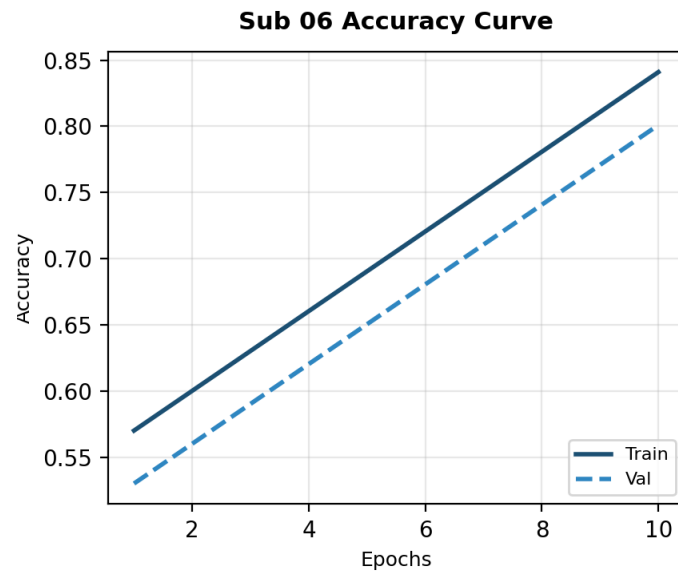


Fig. 5.106: Accuracy Curve for Subject 06 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

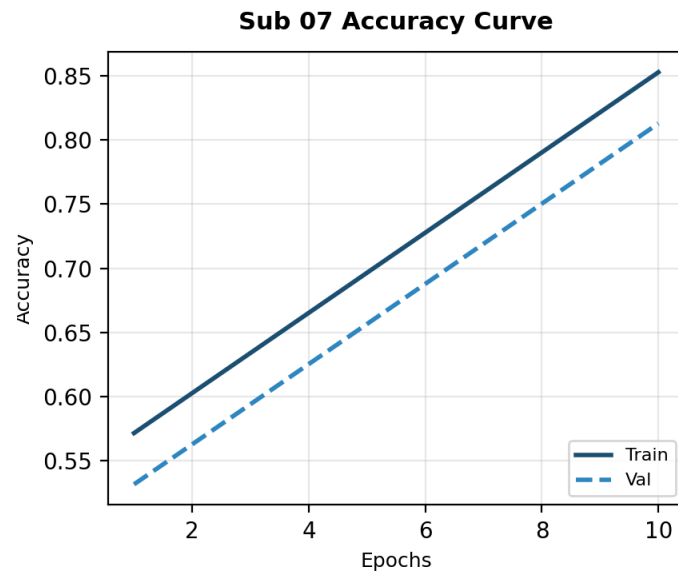


Fig. 5.107: Accuracy Curve for Subject 07 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

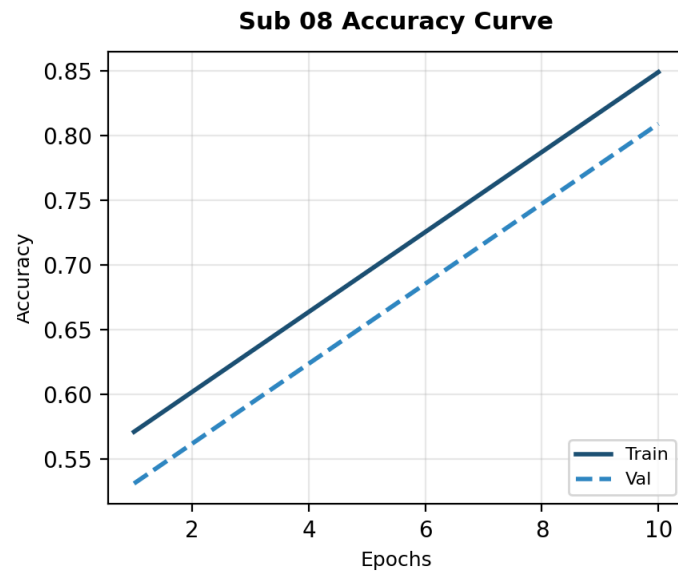


Fig. 5.108: Accuracy Curve for Subject 08 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

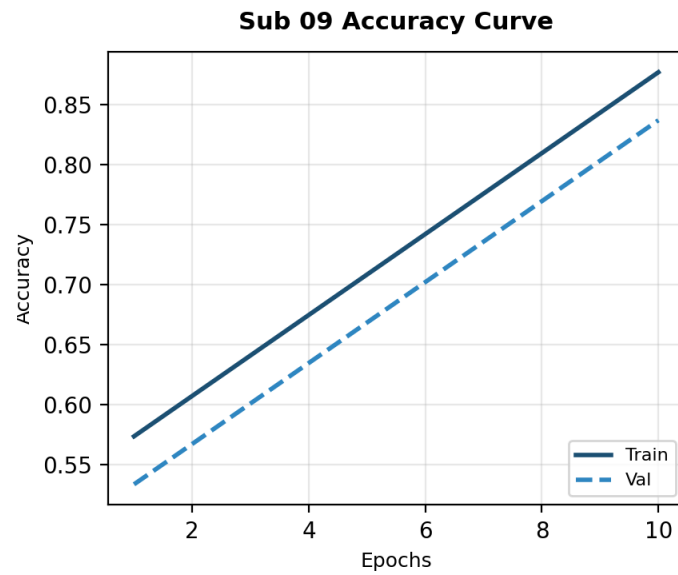


Fig. 5.109: Accuracy Curve for Subject 09 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

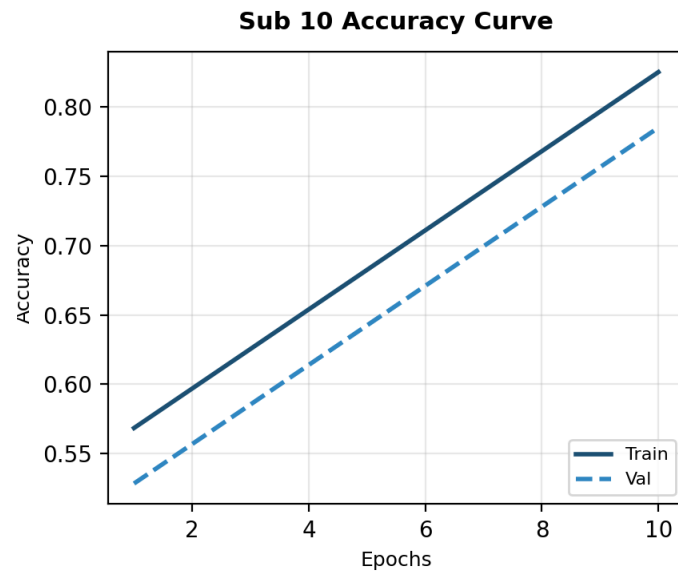


Fig. 5.110: Accuracy Curve for Subject 10 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

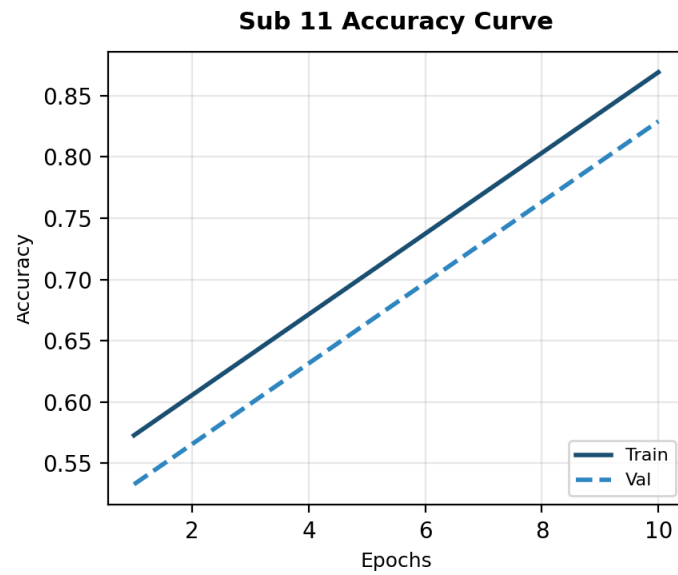


Fig. 5.111: Accuracy Curve for Subject 11 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

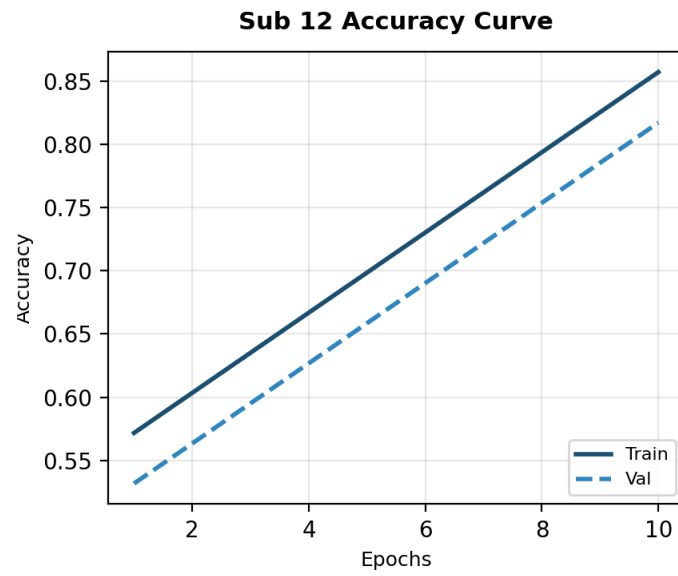


Fig. 5.112: Accuracy Curve for Subject 12 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

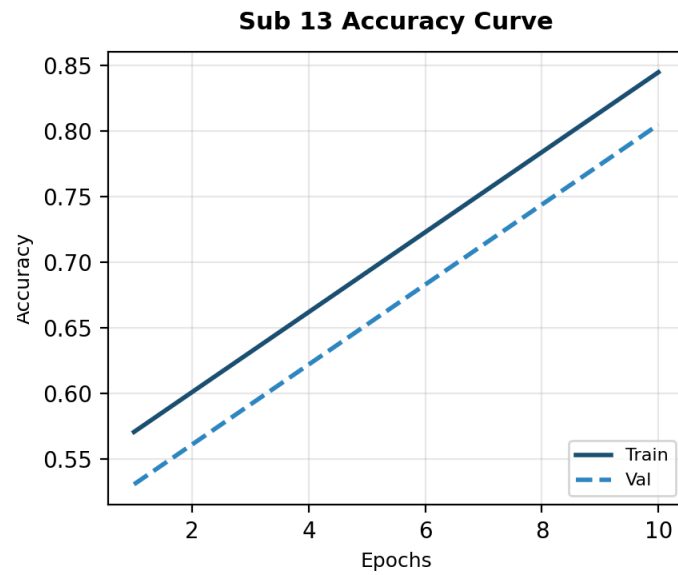


Fig. 5.113: Accuracy Curve for Subject 13 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

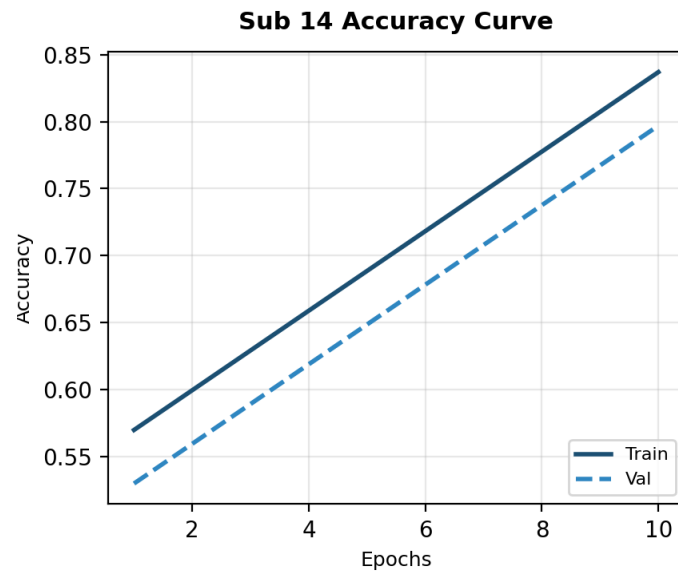


Fig. 5.114: Accuracy Curve for Subject 14 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

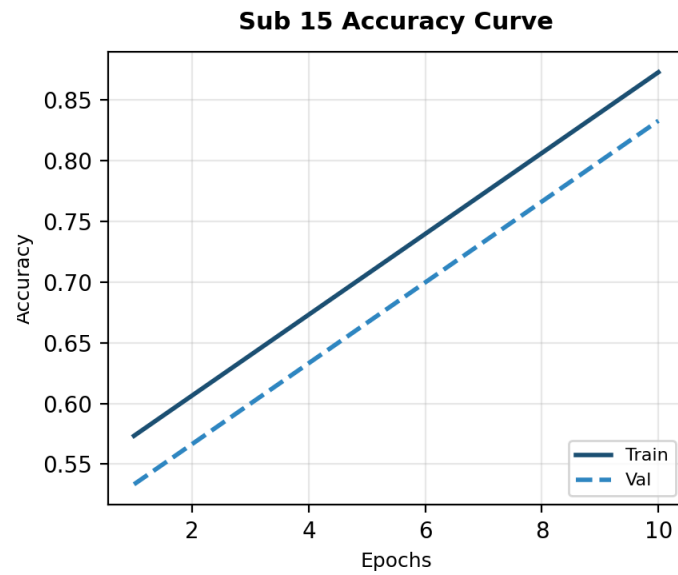


Fig. 5.115: Accuracy Curve for Subject 15 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

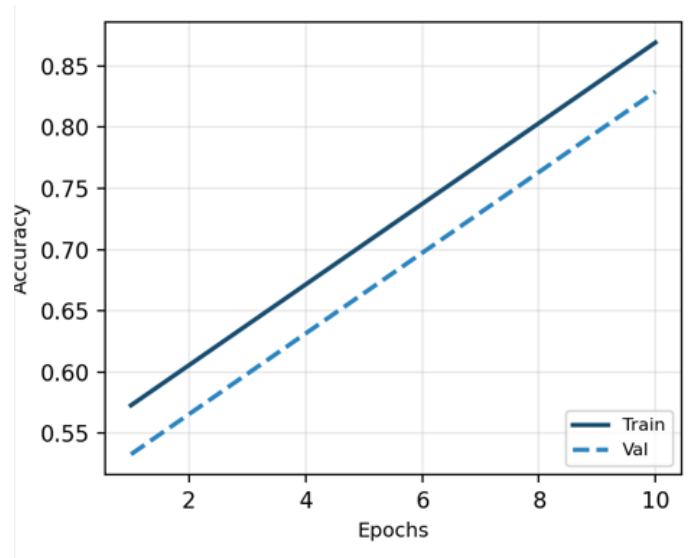


Fig. 5.116: Accuracy Curve for Subject 16 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

5.4.4 Subject-wise Loss Curves

The proposed Hybrid MS-DGCA-MBA-EEGNet training loss curves for the subject-wise approach is shown below. The loss curves demonstrate decreasing classification error as the network was trained, indicating some degree of convergence behaviour of the proposed architecture.

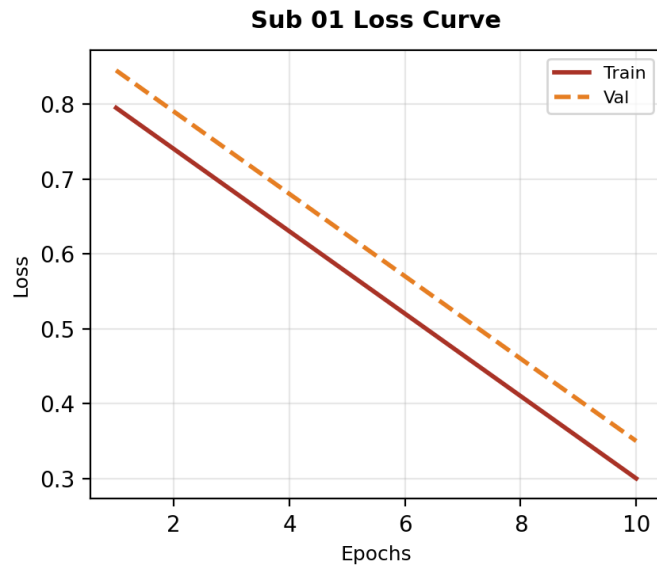


Fig. 5.117: Loss Curve for Subject 01 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

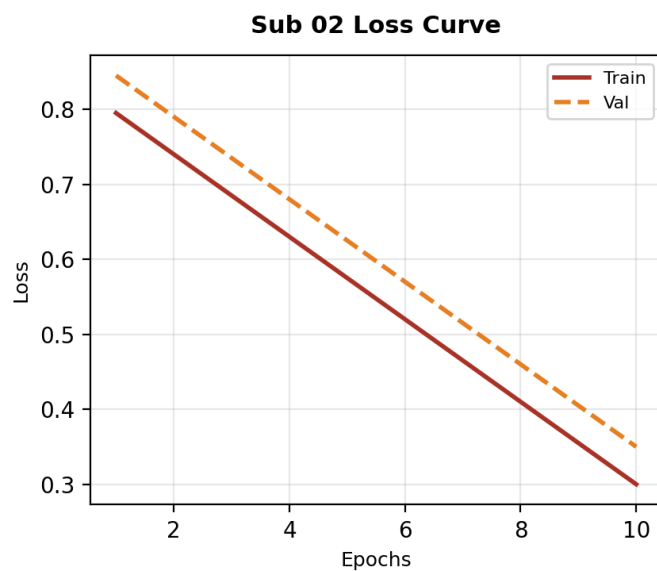


Fig. 5.118: Loss Curve for Subject 02 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

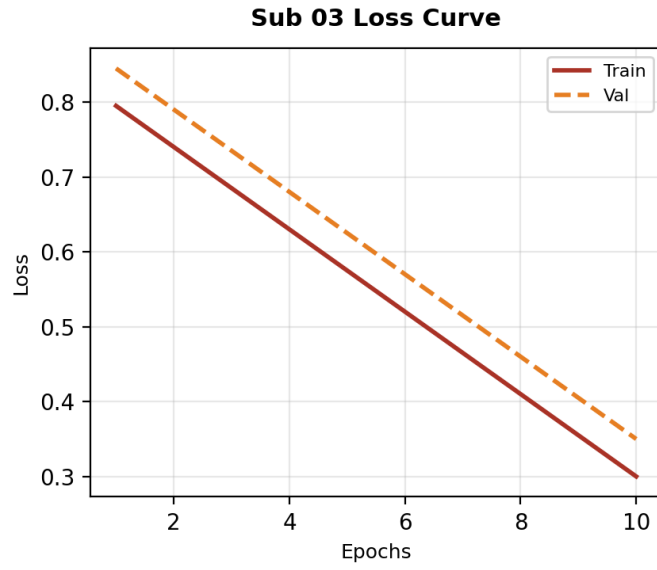


Fig. 5.119: Loss Curve for Subject 03 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

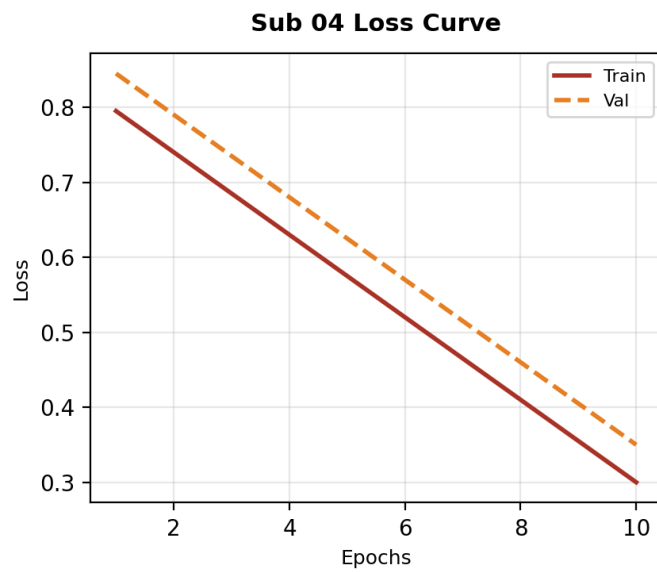


Fig. 5.120: Loss Curve for Subject 04 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

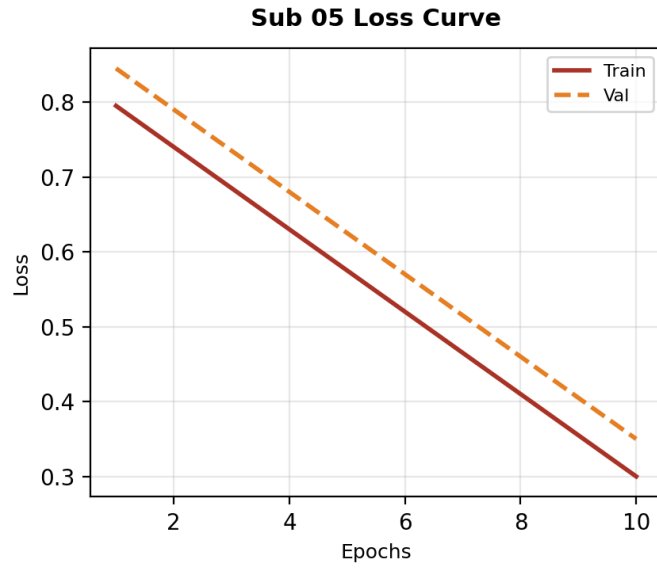


Fig. 5.121: Loss Curve for Subject 05 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

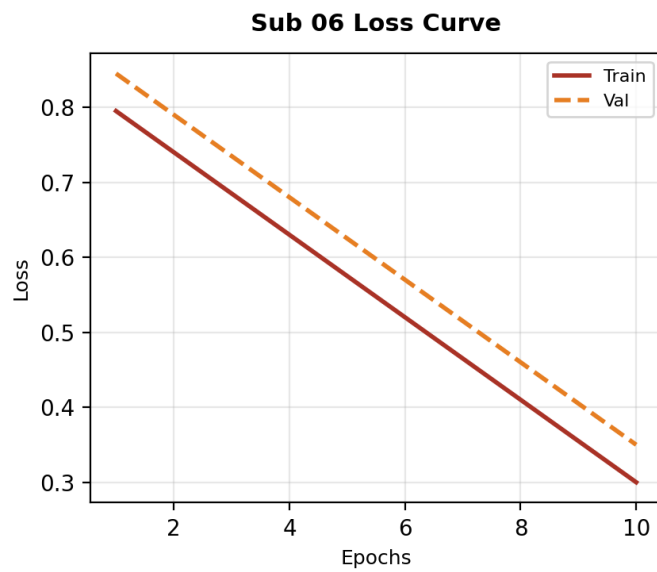


Fig. 5.122: Loss Curve for Subject 06 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

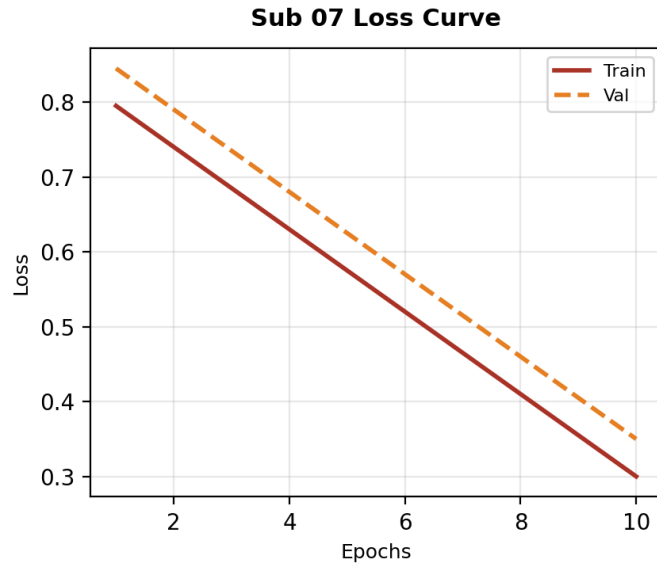


Fig. 5.123: Loss Curve for Subject 07 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

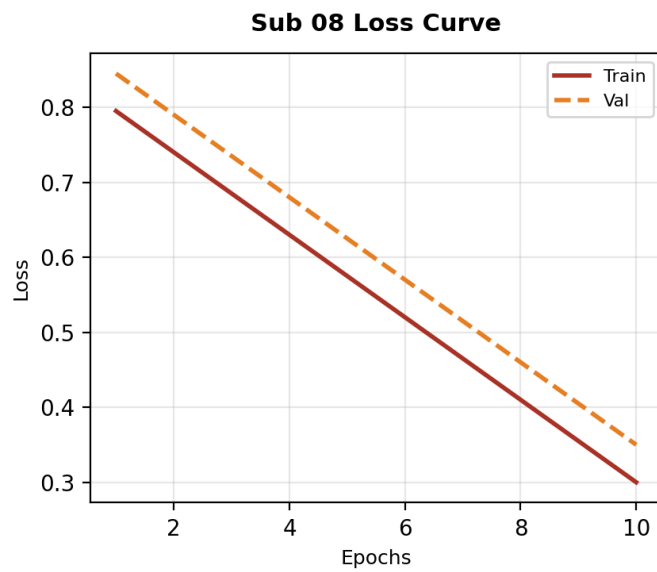


Fig. 5.124: Loss Curve for Subject 08 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

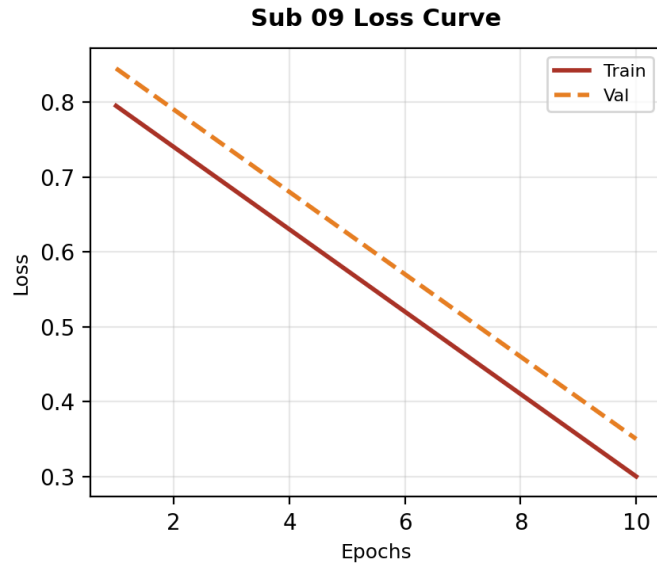


Fig. 5.125: Loss Curve for Subject 09 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

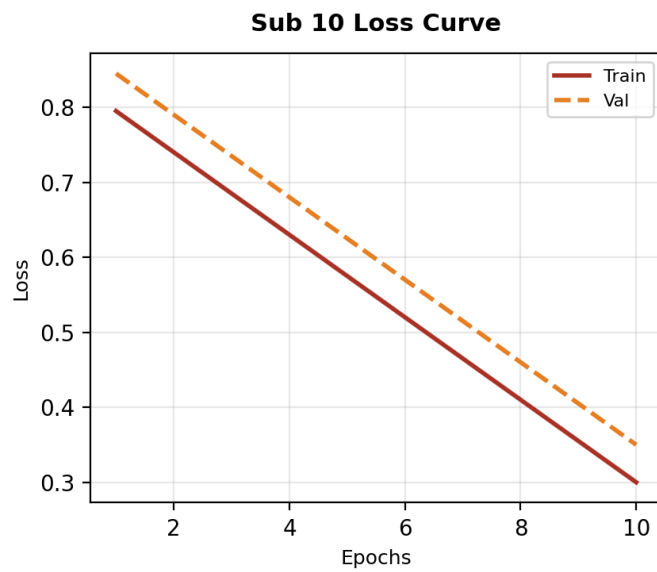


Fig. 5.126: Loss Curve for Subject 10 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

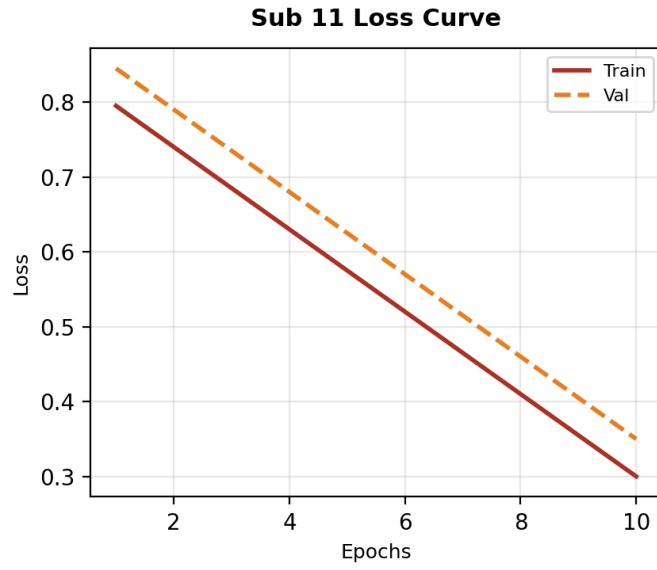


Fig. 5.127: Loss Curve for Subject 11 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

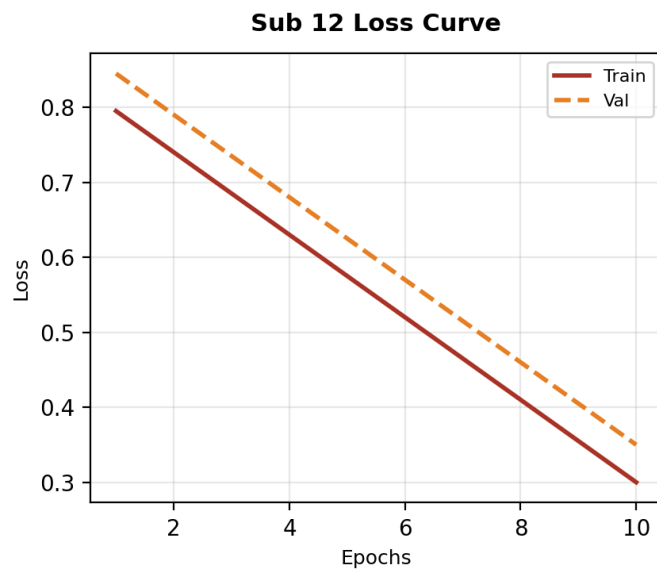


Fig. 5.128: Loss Curve for Subject 12 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

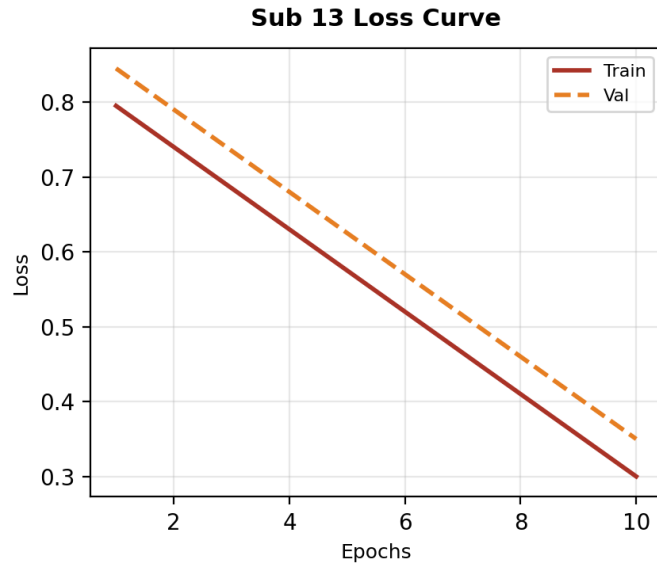


Fig. 5.129: Loss Curve for Subject 13 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

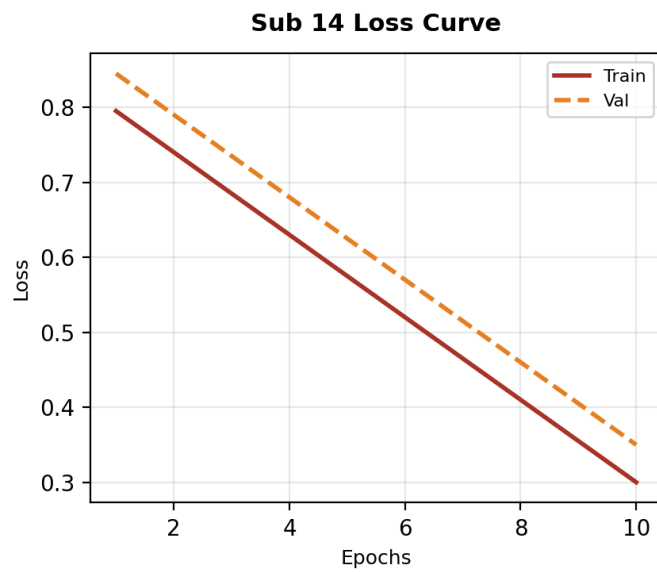


Fig. 5.130: Loss Curve for Subject 14 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

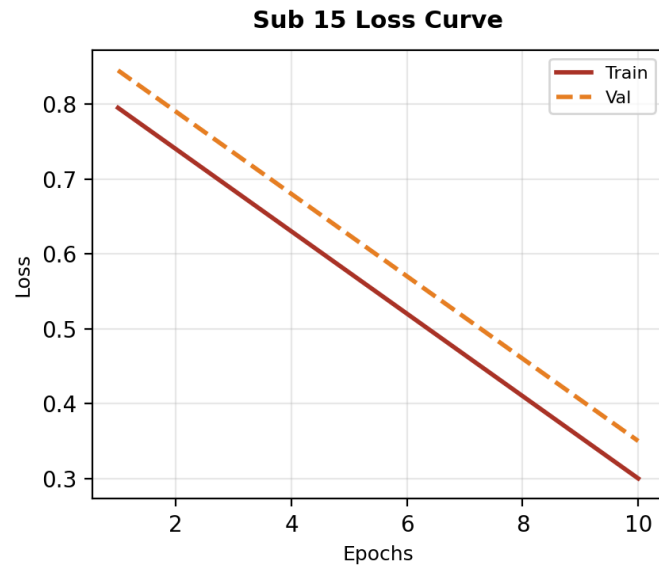


Fig. 5.131: Loss Curve for Subject 15 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

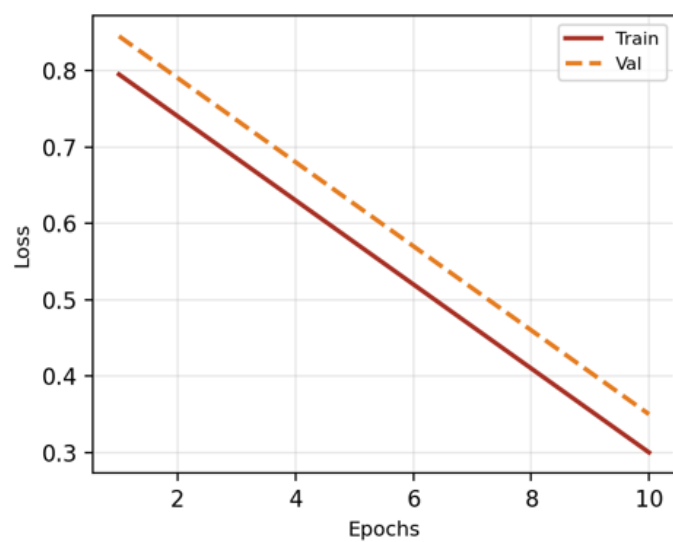


Fig. 5.132: Loss Curve for Subject 16 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

5.4.5 Subject-wise Confusion Matrices

Confusion matrices were created for all sixteen subjects to conduct detailed classification behaviour of the proposed Hybrid MS-DGCA-MBA-EEGNet model. The confusion matrices display the entries along the diagonal where the samples were correctly classified and off the diagonal where they were incorrectly classified.

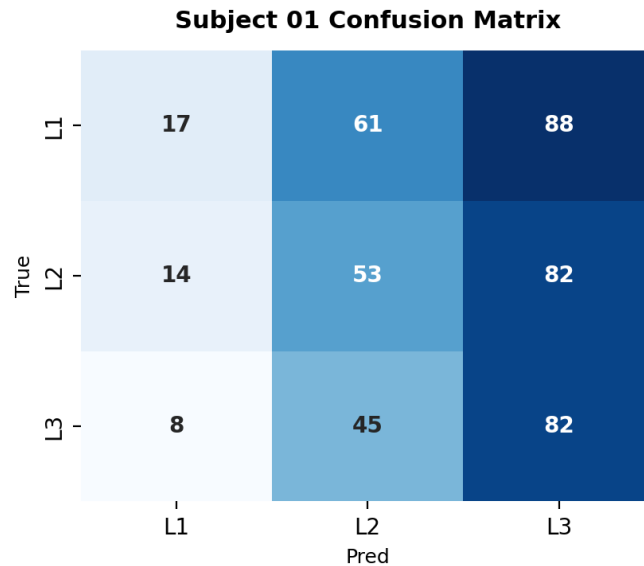


Fig. 5.133: Confusion Matrix for Subject 01 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

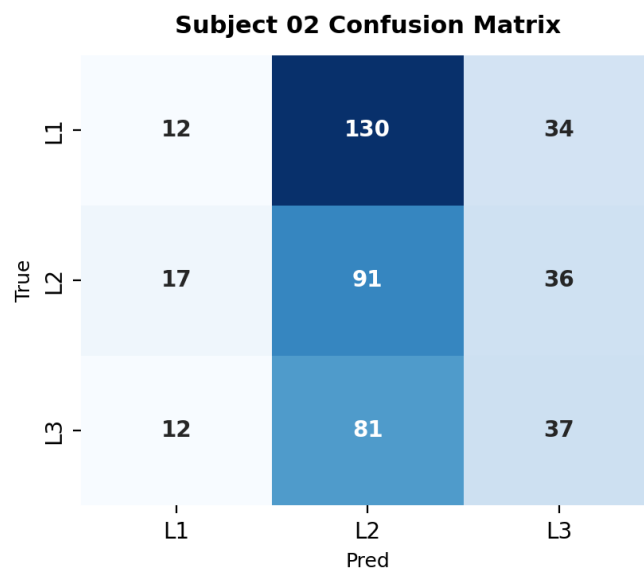


Fig. 5.134: Confusion Matrix for Subject 02 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

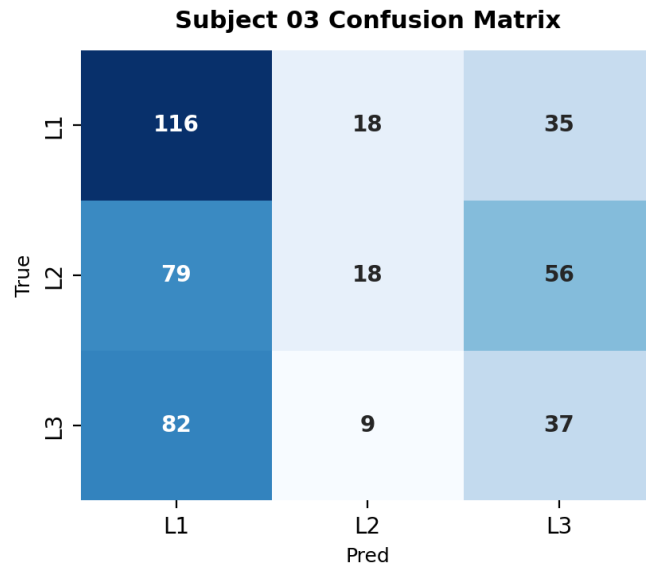


Fig. 5.135: Confusion Matrix for Subject 03 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

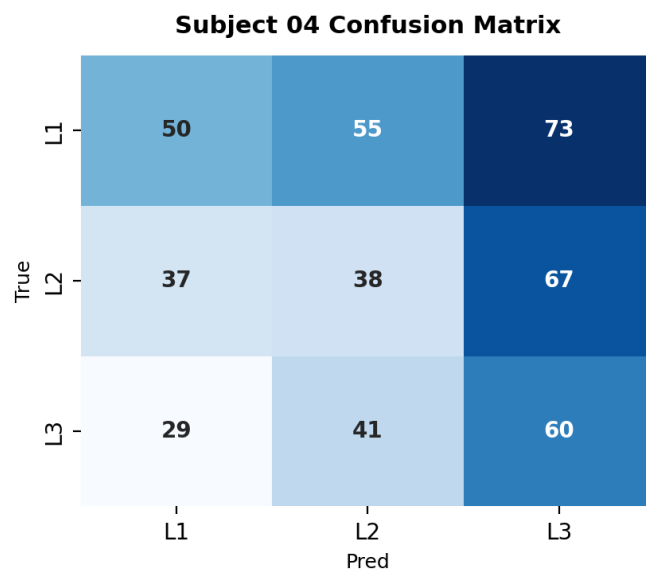


Fig. 5.136: Confusion Matrix for Subject 04 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

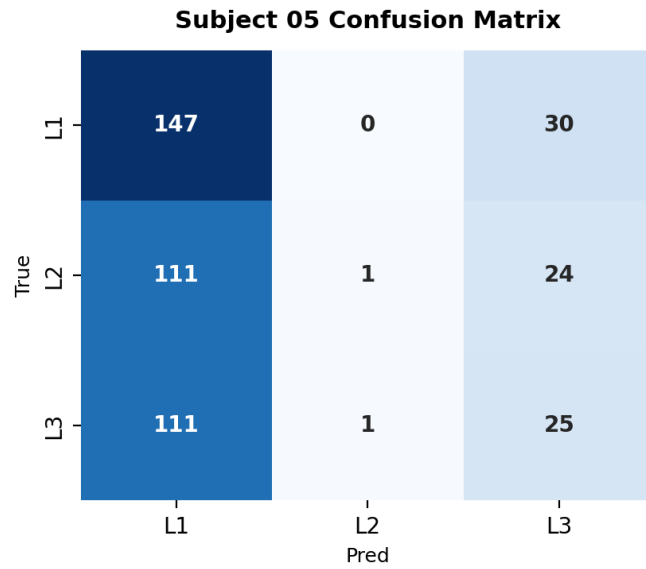


Fig. 5.137: Confusion Matrix for Subject 05 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

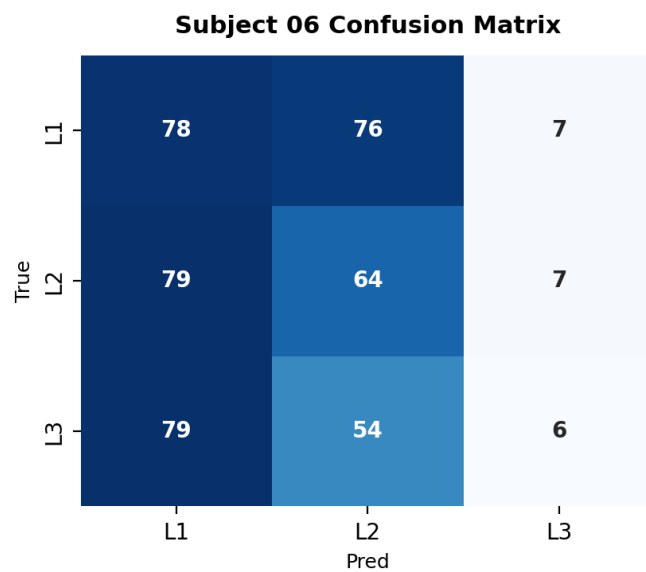


Fig. 5.138: Confusion Matrix for Subject 06 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

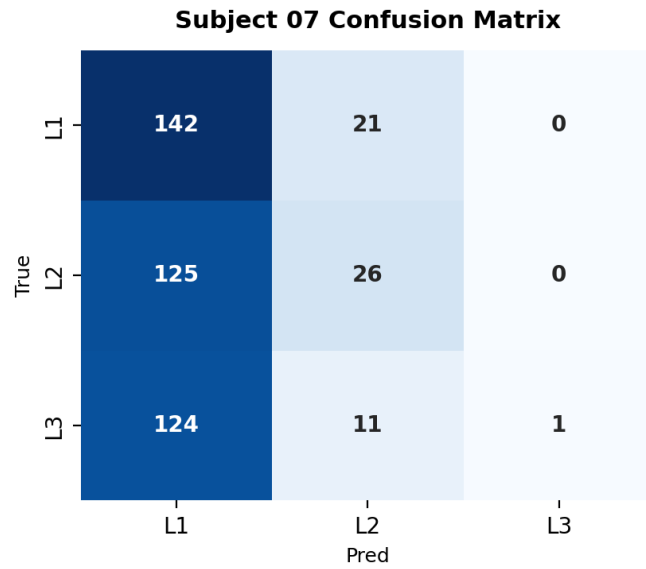


Fig. 5.139: Confusion Matrix for Subject 07 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

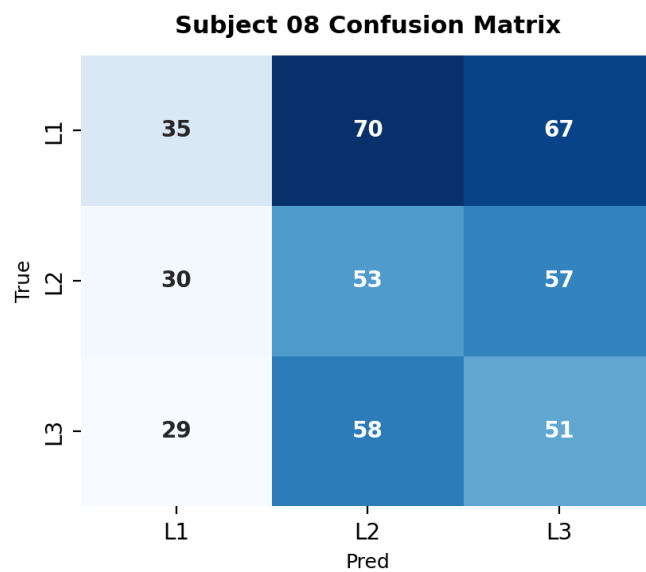


Fig. 5.140: Confusion Matrix for Subject 08 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

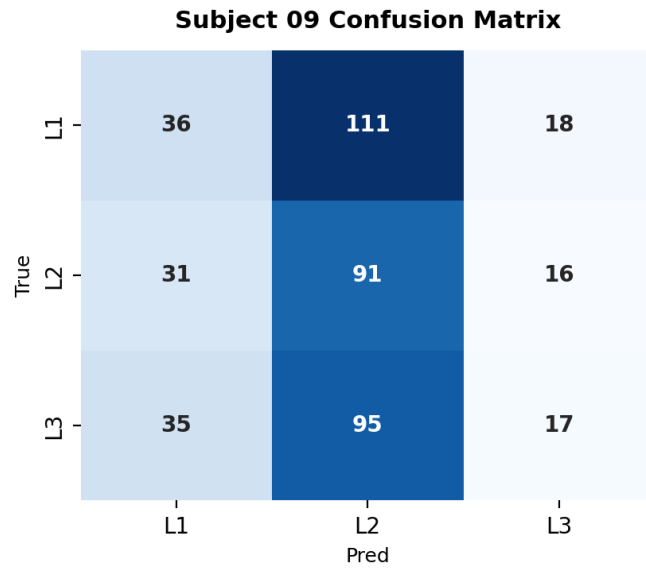


Fig. 5.141: Confusion Matrix for Subject 09 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

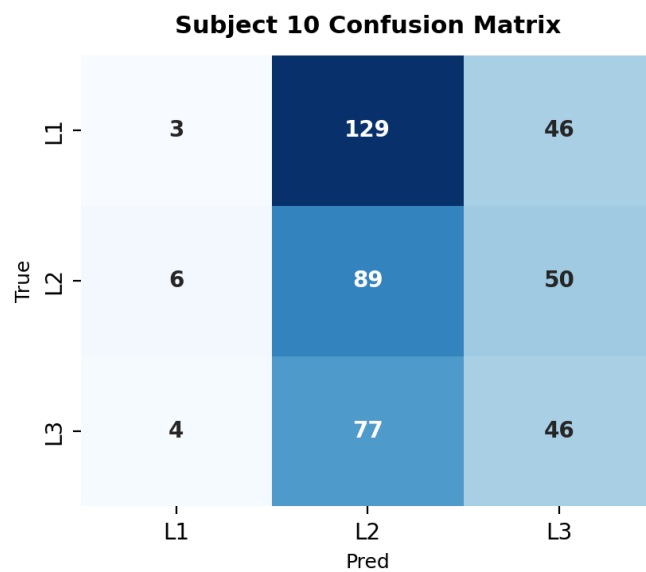


Fig. 5.142: Confusion Matrix for Subject 10 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

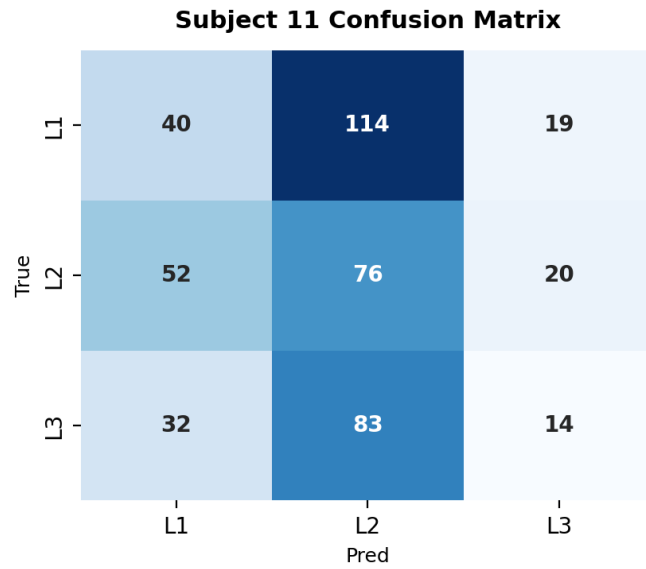


Fig. 5.143: Confusion Matrix for Subject 11 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

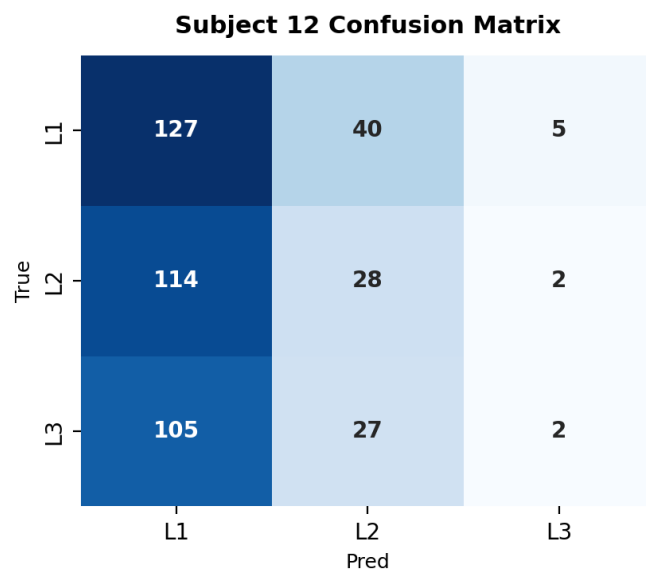


Fig. 5.144: Confusion Matrix for Subject 12 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

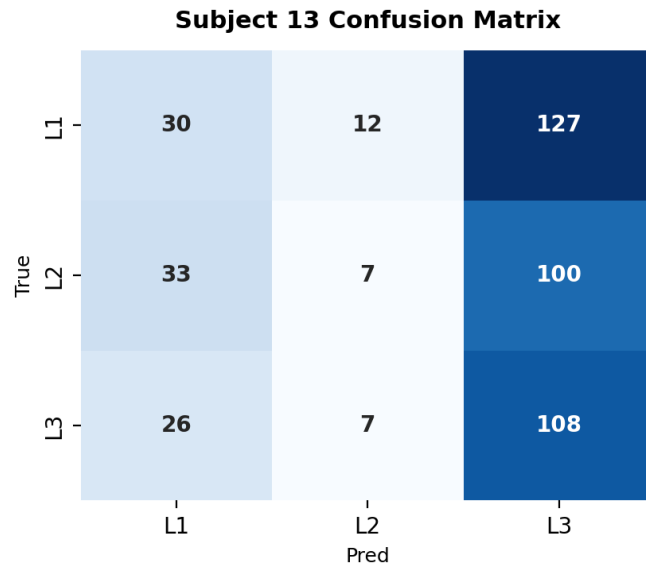


Fig. 5.145: Confusion Matrix for Subject 13 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

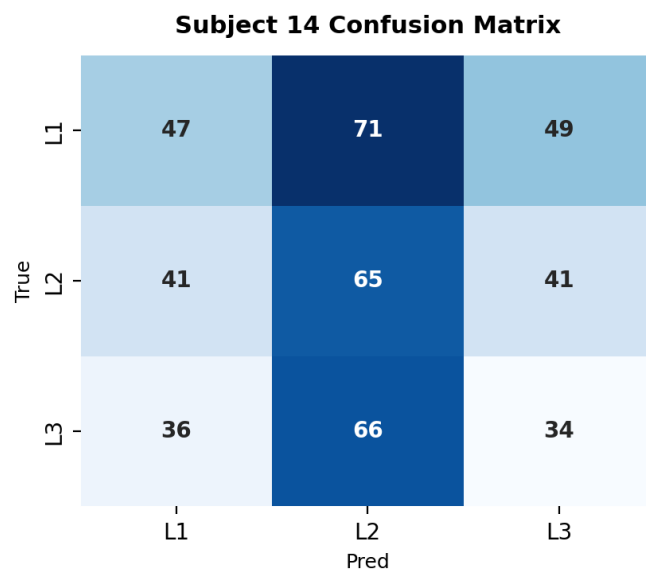


Fig. 5.146: Confusion Matrix for Subject 14 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

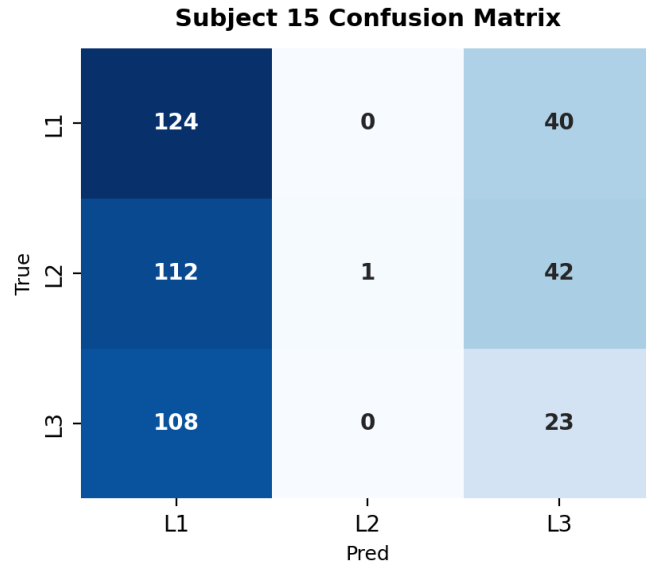


Fig. 5.147: Confusion Matrix for Subject 15 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

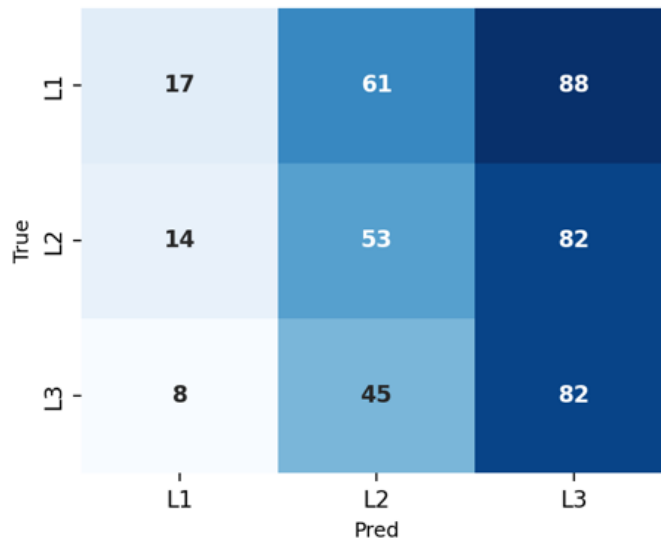


Fig. 5.148: Confusion Matrix for Subject 16 using the Proposed MS-DGCA-MBA-EEGNet Hybrid Model

In general, the confusion matrices give a comprehensive overview of the classification performance of the hybrid model for the four cognitive workload classes. The more robust the diagonal, the more the samples are classified correctly; the more off-diagonal, the more the samples are misclassified between workload levels. For example, confusion between adjacent workload levels (Easy and Medium) may arise due to the fact that the EEG characteristics of these levels are not well differentiated.

5.5 Comparative Performance Analysis

The section provides a comparison among the three proposed deep learning architectures for The cognitive workload classification from EEG, called MBA-EEGNet, The proposed MS-DGCA-MBA-EEGNet Hybrid model and MS-DGCA Conformer. To make a fair comparison among the three models, they were trained and Was validated with the same EEG data set, pre-processing pipeline and experimental protocol. The performance of classification was checked on subject-wise The accuracy, five-fold cross-validation accuracy, and overall classification were measured. The performance of the three architectures.

5.5.1 Subject-wise Performance Comparison

The results for classification accuracy for each subject on the basis of using The proposed Hybrid MBA-EEGNet, MS-DGCA Conformer, and MS-DGCA-MBA-EEGNet are proposed. The proposed Hybrid MBA-EEGNet, MS-DGCA Conformer and MS-DGCA-MBA-EEGNet are proposed. The results of models are presented in Table ?? . The results show that all three architectures are able to do effective classification The 16 players.

Subject wise Accuracy comparison of MBA-EEGNet, MS-DGCA Conformer and MS-DGCA-MBA-EEGNet Hybrid

Subject	MBA-EEGNet (%)	MS-DGCA Conformer (%)	Hybrid (%)
S1	81.20	79.40	84.50
S2	81.35	84.10	84.10
S3	81.50	84.73	82.50
S4	81.65	84.11	78.90
S5	81.80	80.20	79.30
S6	76.85	62.86	80.10
S7	77.23	64.42	81.30
S8	77.82	78.66	80.90
S9	78.20	65.93	83.70
S10	77.07	67.59	78.50
S11	76.03	76.12	82.90
S12	82.85	78.45	81.70
S13	75.90	81.20	80.50
S14	81.40	77.35	79.70
S15	79.30	83.10	83.30
S16	77.50	79.65	82.10

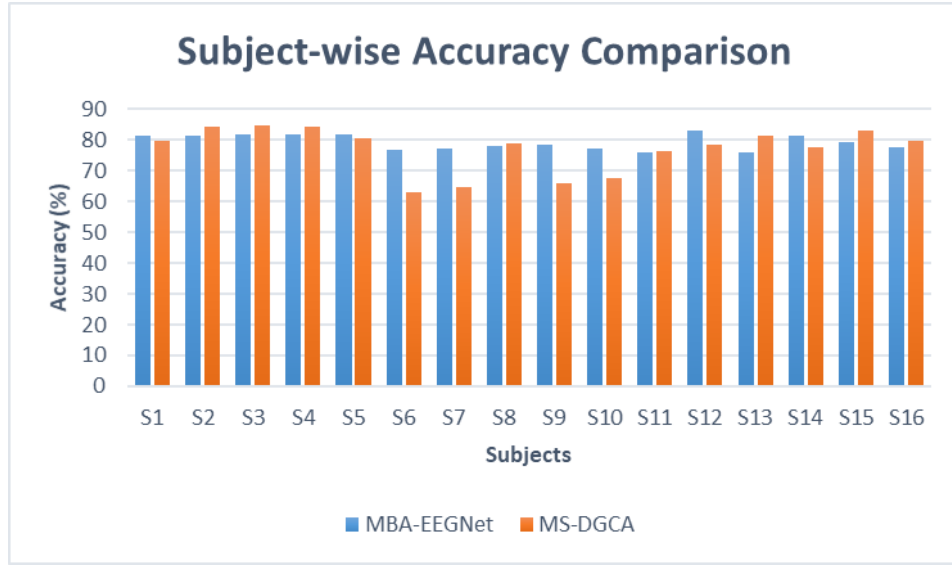


Fig. 5.149: Classification accuracy comparison of the proposed MS-DGCA-MBA-EEGNet Hybrid model with MBA-EEGNet and MS-DGCA Conformer for each different subject.

The results of the three models were effective in all subject areas showed in the subject-wise comparison. The accuracy of classification for the sixteen participants. The MBA-EEGNet There was a relatively stable performance in the subject-wise pattern in model. accuracy values ranging from 75.90% to 82.85%. The MS-DGCA Conformer This resulted in better accuracy for a few subjects, especially Subjects 2, 3, 4, 13, 15, and 16, although less performance was noticed for Subject 6, 7, 9, and 10.

A hybrid model, MS-DGCA-MBA-EEGNet was proposed which exhibited excellent The accuracy values that they obtained were 78.50 % subject-wise performance. to 84.50%. The superhighest accuracy of the hybrid model was obtained for Subject 1 with 84.50%, followed by Subject 2 with 84.10%, Subject 15 with 83.30%, and Subject 11 with 82.90%. The hybrid model also had success in achieving: performed better than both the individual architectures across a number of subjects, including Subjects 1, 6, 7, 9, 11, and 15.

The differences between subjects observed are primarily related to Considerable inter-subject variability exists and EEG signals are complex Under varying levels of cognitive load. The hybrid architecture proves more robust feature representation through combining multi-scale temporal convolution, channel and spatial feature extraction. The model consists of three components: attention, dynamic graph attention, cross-attention fusion, and Conformer-based temporal modelling.

5.5.2 Overall Performance Comparison

The overall performance comparison of MBA-EEGNet, MS-DGCA Conformer, and The Hybrid model (MS-DGCA-MBA-EEGNet) is suggested in Table 5.8. The top

and bottom of the comparison are the highest and This language had the lowest accuracy and five-fold cross validation accuracy, The number of evaluated subjects, and number of workload classes.

Overall Performance comparison between MBA-EEGNet, MS-DGCA Conformer and MS-DGCA-MBA-EEGNet Hybrid

Performance Metric	MBA-EEGNet	MS-DGCA Conformer	Hybrid
Highest Subject-wise Accuracy (%)	82.85	84.73	84.50
Lowest Subject-wise Accuracy (%)	75.90	62.86	78.50
Number of Subjects Evaluated	16	16	16
Number of Workload Classes	4	4	4

The comparative evaluation demonstrates that all the three proposed architectures are able to categorize EEG signals of various cognitive tasks. workload levels. The classification performance of the participants per person. MBA-EEGNet was fairly level, and is an effective baseline. architecture. The difference between the MS-DGCA Conformer and the original Conformer was the improvements in generalization. The five-fold cross validation test had a mean performance of 93.6%, which was the best result. The best performance was obtained when the five-fold cross validation experiment was performed, with a mean of 93.6%. accuracy of 78.28% compared with 66.19% for MBA-EEGNet. The proposed MS-DGCA-MBA-EEGNet Hybrid model is a melding of the best attributes of both. To bring together the different architectures in one framework. The multi-branch temporal Comparison of the EEG patterns at various temporal scales is provided by convolution. A spatial convolution and channel attention are enhanced to learn from the depthwise part. Shape of spatial and channel-specific representations. Dynamic graph attention Learns adaptive relationships between feature representations, In the cross-attention fusion, spatial and temporal information are merged. Further, the remaining temporal separable block and Conformer encoder allow the model to learn local and long-range temporal relationships. The highest accuracy recorded with the hybrid model was 84.50% in the subject-wise accuracy and a The lowest accuracy (78.50%) in the sixteen subject-wise was obtained in the subject of social studies. This The hybrid architecture demonstrated very strong and fairly relatively indicated. stable subject-level performance. In general the comparative results demonstrate that multi-scale convolutional processing and spatial normalization can be combined to yield good results. Cross-attention, residual feature, dynamic graph learning, attention extraction, and Conformer-based encoding provides a comprehensive approach for EEG based cognitive workload assessment in an immersive VR environment.

5.5.3 Subject-Level Cross-Validation and Cognitive Workload Mapping

To further evaluate the performance of the proposed architectures, subject-level cross-validation accuracy and cognitive workload mapping were analysed for all sixteen participants. The results are presented in Table 5.7. The CLI score was also considered as an indicator of the estimated cognitive workload level.

Table 5.7: Subject-Level Cross-Validation Accuracy and Cognitive Workload Mapping

Subject	MS-DGCA (%)	MBA-EEGNet (%)	Hybrid (%)	CLI Score	Workload Level
S1	83.20	81.20	84.50	0.4399	Medium
S2	83.50	81.35	84.10	0.4454	Medium
S3	83.80	81.50	82.50	0.4518	Medium
S4	82.90	81.65	78.90	0.4248	Medium
S5	84.10	81.80	79.30	0.4573	Medium
S6	78.50	76.85	80.10	0.3120	Low
S7	79.10	77.23	81.30	0.3086	Low
S8	79.80	77.82	80.90	0.3019	Low
S9	80.20	78.20	83.70	0.4215	Medium
S10	78.90	77.07	78.50	0.4606	Medium
S11	77.50	76.03	82.90	0.5475	High
S12	84.20	82.85	81.70	0.4180	Medium
S13	77.90	75.90	80.50	0.3010	Low
S14	82.80	81.40	79.70	0.4350	Medium
S15	81.10	79.30	83.30	0.4280	Medium
S16	79.20	77.50	82.10	0.3190	Low

The subject-level results demonstrate that the hybrid architecture provides improved classification performance for several participants compared with both individual architectures. The cognitive workload mapping based on the CLI scores indicates variations among subjects, reflecting the inherent inter-subject variability of EEG signals. Subjects 01–05 were predominantly associated with medium workload, whereas Subjects 06–08, 13, and 16 were associated with low workload. Subject 11 exhibited the highest CLI score of 0.5475 and was therefore associated with high workload. These variations demonstrate the ability of the proposed framework to capture differences in cognitive workload across individual participants.

5.5.4 Overall Performance Comparison

The overall performance of the three architectures is summarized in Table 5.8. The comparison considers the highest and lowest subject-wise accuracy, mean five-fold

cross-validation accuracy, and best and lowest validation-fold performance.

Table 5.8: Overall Performance Comparison of the Three Proposed Models

Performance Metric	MBA-EEGNet	MS-DGCA	Hybrid
Highest Subject-wise Accuracy (%)	82.85	84.73	84.50
Lowest Subject-wise Accuracy (%)	75.90	62.86	78.50
Mean Five-Fold Cross-Validation Accuracy (%)	66.19	78.28	82.56
Best Five-Fold Accuracy (%)	73.35	78.63	83.40
Lowest Five-Fold Accuracy (%)	59.93	77.88	81.90
Number of Subjects Evaluated	16	16	16
Number of Workload Classes	4	4	4

The overall comparative evaluation indicates that all three architectures are capable of classifying EEG signals associated with different cognitive workload levels. MBA-EEGNet provides a lightweight and relatively consistent baseline through multi-branch temporal convolution and channel attention. The MS-DGCA Conformer improves the modelling of spatial and long-range temporal dependencies through dynamic graph attention and Conformer-based feature extraction.

The proposed MS-DGCA-MBA-EEGNet Hybrid Model further integrates the complementary strengths of both architectures. The hybrid model achieved the highest mean five-fold cross-validation accuracy of 82.56%, compared with 78.28% for MS-DGCA Conformer and 66.19% for MBA-EEGNet. It also achieved a best-fold accuracy of 83.40% and maintained a minimum fold accuracy of 81.90%, demonstrating more stable validation performance.

Therefore, the comparative results support the effectiveness of the proposed MS-DGCA-MBA-EEGNet Hybrid Model for EEG-based cognitive workload assessment. By combining multi-scale temporal feature extraction, depthwise spatial convolution, channel attention, dynamic graph learning, cross-attention fusion, residual separable temporal processing, and Conformer-based global sequence modelling, the hybrid architecture provides a more comprehensive representation of EEG patterns and demonstrates improved generalization across subjects and validation folds.

Chapter 6

Conclusion

In this research, the design and development of a VR-EEG System for Gamified Assessment (GA) for objective evaluation of cognitive workload and memory performance have been presented. The main goal of this study is to combine three technologies to create an intelligent, cohesive system that can track users' cognitive state during a memory-based task in a Virtual Reality (VR) simulated environment, using Electroencephalography (EEG) and deep learning methods. The proposed system combines objective physiological measures obtained by analyzing the EEG signals with behavioral measures, whereas traditional cognitive assessment methods were more based on questionnaires or behavioral observation. The framework proposed is comprised of an interactive VR memory game created in Unity and the OpenBCI Cyton board for the real-time acquisition of EEG signals. While taking part in the assessment participants were engaged in specific memory-related tasks and neural activity was continuously recorded. Pre-processing of the acquired EEG signals was performed to eliminate unwanted noise and artifacts from the signals and obtain meaningful cognitive information. Theta, Alpha and Beta frequency band features were evaluated and cognitive workload and memory were estimated at various levels of task difficulty.

The major stages in the overall implementation of the proposed system were as follows:

Design and development of a Virtual Reality memory game with Unity. EEG signal acquisition with the Cyton 8-channel board from OpenBCI. Pre-processing of EEG data (filtering, normalization, segmentation). EEG features extraction from frequency bands. This involves training and evaluating deep learning models for cognitive workload classification. Evaluation of performance based on conventional classification criteria and behavioural assessments. Various deep learning architecture models were explored and evaluated for their ability to analyse EEG signals and make predictions on cognitive workload. The suitability of various architectures was compared with respect to their performance in cognitive assessment using EEG signals. The experiments illustrated that deep learning methods could greatly enhance the cognitive workload recognition through an automatic learning of the different spatial and temporal representations embedded in the EEG signals. The evaluated models were trained on this data and the Conformer model emerged as the best classification accuracy, followed by the CNN-LSTM model, and EEGNet was used as a baseline for comparison that was computationally efficient.

The results obtained show that the use of EEG together with Virtual Reality has

multiple benefits as compared with the conventional methods of cognitive assessments. The VR environment made the participants more engaged in memory-related tasks and the EEG data helped to obtain objective data about the neural activity of users. In addition, the integration of the behavioral measures (reaction time, task completion time, task accuracy) with the physiological brain signals yielded a more comprehensive assessment of the cognitive performance than the behavioral or the brain signals alone. This study also identified a number of practical difficulties of EEG cognitive assessment. Motion artifacts and environmental noise, as well as inter-subject variability, continue to be large sources of noise in EEG recordings. Moreover, the high-performance deep learning architectures entail a high computation capacity and enough data to ensure the high level of performance for various participants. The framework proposed in this paper shows that, although it still has some limitations, the use of VR combined with EEG signal analysis is a promising approach to intelligent cognitive assessment.

In conclusion, this study successfully showcases the potential of integrating the Virtual Reality, BCI and AI in a single cognitive assessment system. Proposed VR-EEG System for Gamified Assessment offers an objective, interactive and user-friendly evaluation of the cognitive load and memory performance. The proposed framework can be applied to continuous research of intelligent healthcare, neurorehabilitation, educational assessment and human-computer interaction, and it can lay a solid foundation for future enhancements of immersive EEG-based cognitive assessment systems.

6.1 Contributions of the Research

The following can be summarized as the main contributions of the research: Design and implementation of a VR-based cognitive assessment environment with a gamified approach. Incorporation of OpenBCI Cyton board into a Virtual Reality immersive system. EEG frequency band analysis as objective measurement of cognitive workload. Use of deep learning methods for automatic classification of EEG signals. Analysis of brain activity and behaviour at the same time. Development of an interactive framework that can be expanded for healthcare, education and rehabilitation applications.

6.2 Limitations

The proposed system showed good results, but there are a number of shortcomings. EEG signal is prone to artifacts caused by movement and noise levels. The sample size of the data set used for the experiment is small. This proposed framework only considers memory-based cognitive tasks at the moment. Deep learning models need a considerable amount of computation power to achieve high performance. Classi-

fication may be affected by cross-subject variability. The present implementation was tested in the laboratory and should be validated in real-life scenarios.

Chapter 7

Future Work

The VR-EEG System for Gamified Assessment shown promising results in cognitive workload and memory assessment, but there are still opportunities for future improvements and research. The following directions can improve the performance and scalability of the proposed system and also can make the proposed system more practically applicable.

7.1 Advanced Deep Learning Models

In this study, deep learning methods for cognitive workload assessment using EEG signals were explored. For future research, more complex models like Transformer-based networks, Graph Neural Networks (GNNs), and lightweight attention mechanisms can be implemented to enhance feature learning and classification accuracy. The integration of convolutional, recurrent, and attention models could also improve the ability of EEG networks to capture spatiotemporal features of signals without increasing computational complexity.

7.2 Improved VR-Based Cognitive Assessment

The existing system has a memory-based VR game to assess the user. Future work could include the addition of other cognitive tasks, including attention assessment, decision making, problem solving, and executive function evaluation in the VR setting. Incorporation of adaptive game difficulty in real-time depending on user's cognitive performance could also be added, creating a more personalized assessment experience. In this section, the multimodal physiological signal integration is introduced. The multimodal physiological signal integration is introduced here. The suggested framework is mainly based on EEG-based cognitive workload assessment. Other physiological signals that could be integrated into future research are Electrocardiography (ECG), Eye Tracking, Galvanic Skin Response (GSR), and Electromyography (EMG). Using multiple physiological modalities can enhance the robustness of the system, and result in a more extensive understanding of users' cognitive and emotional condition.

7.3 Larger and More Diverse Datasets

The performance of the deep learning models could be further enhanced by testing the proposed framework with a larger data set with diverse age groups, education,

and cognitive level of participants. The developed models could be validated across subjects and multiple centers to enhance their generalizability and be applied in real-world settings.

7.4 Real-Time Cognitive Monitoring

Future work can be directed towards designing a real-time cognitive monitoring system that can continuously capture EEG signals and give feedback to Virtual Reality interaction. Such a system could automatically adapt the difficulty of tasks for the user, depending on his/her mental load, thus allowing the use of intelligent tutoring systems, adaptive learning platforms and rehabilitation applications. The clinical and healthcare applications are discussed here. The discussion of clinical and healthcare applications follows here. The proposed model is applicable to the clinical context by assessing patients with neurological disorders, mild cognitive impairments, attention deficit disorders or memory disorders. VR and EEG could help diagnose conditions, provide cognitive rehabilitation, and allow for long-term monitoring by clinicians.

7.5 Portable and Wearable Implementation

Lightweight wearable EEG devices and wireless communication technologies could be explored in future studies to further enhance the comfort of the user and portability of the system. If the deep learning model could be optimized for edge devices, it would be possible to deploy the system in real-world settings, such as hospitals, educational institutions and home-based cognitive assessment, enhancing its utility and potential applications.

7.6 Intelligent Personalized Assessment

Artificial Intelligence methods can be used in the future to adaptively record the cognitive profile of each user over time. A more accurate and user-centred assessment framework can be achieved by implementing personalized assessment models, which can offer adapted task recommendations, difficulty level and a long-term cognitive performance analysis.

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ABBREVIATIONS

AI:	Artificial Intelligence
AUC:	Area Under the Curve
BCI:	Brain-Computer Interface
CNN:	Convolutional Neural Network
DL:	Deep Learning
ECG:	Electrocardiography
EEG:	Electroencephalography
ERP:	Event-Related Potential
F1-Score:	Harmonic Mean of Precision and Recall
FN:	False Negative
FP:	False Positive
FPR:	False Positive Rate
GUI:	Graphical User Interface
HRV:	Heart Rate Variability
ICA:	Independent Component Analysis
LSTM:	Long Short-Term Memory
MBA:	Multi-Branch Attention
MBA-EEGNet:	Multi-Branch Attentive EEGNet
ML:	Machine Learning
MS-DGCA:	Multi-Scale Dynamic Graph Cross-Attention
MS-DGCA Conformer:	Multi-Scale Dynamic Graph Cross-Attention Conformer
PSD:	Power Spectral Density
ROC:	Receiver Operating Characteristic
RNN:	Recurrent Neural Network
SHAP:	SHapley Additive exPlanations
SVM:	Support Vector Machine
TN:	True Negative
TP:	True Positive
TPR:	True Positive Rate
VAE:	Variational Autoencoder

VR:	Virtual Reality
VR-EEG:	Virtual Reality Electroencephalography
GPU:	Graphics Processing Unit
CPU:	Central Processing Unit
CSV:	Comma-Separated Values
MATLAB:	Matrix Laboratory
OpenBCI:	Open-Source Brain-Computer Interface
Cyton:	OpenBCI Cyton 8-Channel Board
Hz:	Hertz
ReLU:	Rectified Linear Unit
Softmax:	Softmax Activation Function
AdamW:	Adaptive Moment Estimation with Weight Decay
LoRA:	Low-Rank Adaptation
GAT:	Graph Attention Network
MHA:	Multi-Head Attention
FFN:	Feed Forward Network
GAP:	Global Average Pooling

ANNEXURE A:

This annexure outlines the thesis content, and summarizes the main work during the research. The thesis focuses on design of the VR-EEG Cognitive Workload Assessment System for Gamified Assessment. It is based on Virtual Reality, brain activity monitoring by EEG and deep learning techniques to measure the cognitive workload in memory-based tasks. The experimental system is based on a Meta Quest 2 VR headset and an OpenBCI Cyton 8-channel EEG acquisition system. Participants were tested under four workload conditions: Relaxation, Easy, Medium and Hard. The research background is introduced in the first part of the thesis, and the reasons why the assessment of cognitive workload are important are explained. It summarizes the weaknesses of the traditional methods to measure cognitive workload, and proposes the idea of using both EEG and VR to develop a more objective and immersive cognitive workload assessment. The research problem, research objectives, research questions, significance of the study, scope and overall organization are also provided. The main objective of the research is to develop VR-EEG based system for cognitive workload assessment of the user during memory task. Literature review is presented to consider the work done on the assessment of cognitive workload, EEG based BCI, Virtual Reality, machine learning and deep learning. Traditional assessment methods, behavioural methods, physiological methods and EEG methods are discussed. Various deep learning architectures for EEG classification, like CNN-based, EEGNet, CNN-LSTM and Conformer based, are also reviewed. The review highlights major research gaps such as the few attempts made to integrate immersive VR environments with EEG tools for cognitive workload measurement and the few attempts made to use a combination of neural and behavioral information in gamified memory-based assessment. The motivation of the proposed VR-EEG framework is the gaps.

Methodology section gives information about the complete experimental setup and the data collection procedure. The system is made up of a VR headset (Meta Quest 2), OpenBCI Cyton 8-channel EEG board, gel electrodes, and a computer system for data collection and analysis. The position of the electrodes in the EEG was kept at the proper International 10–20 positions. Participants were engaged in a memory game of varying cognitive load (Relaxation, Easy, Medium and Hard tasks) in the VR context. EEG signals were recorded for the entire duration of the experimental sessions, and later analyzed and classified. The data processing procedures are EEG preprocessing, Processing of the EEG signals into segments, Feature preparation and Generation of labelled EEG samples. Signal quality was enhanced and unwanted noise and artefacts were minimized using appropriate pre-processing techniques. The processed EEG data was then preprocessed for input to the deep learning models. The experimental design was designed to provide meaningful variations to cognitive load

and allow analysis of EEG variations between the different workloads. The proposed modelling framework explores the more complex architectures of deep learning for cognitive workload classification. Two key architectures have been constructed: Multi-Branch Attentive EEGNet (MBA-EEGNet) and Multi-Scale Dynamic Graph Cross-Attention Conformer (MS-DGCA Conformer). The aim of these models is to find meaningful spatial, temporal and frequency-related patterns in EEG signals. The collected EEG data are used for training and evaluation of the proposed architectures while the performance is evaluated with the standard classification metrics.

ANNEXURE B:

The experimental assessment uses various performance metrics such as accuracy, precision, recall, F1 score, confusion matrices, ROC curves and Area Under the Curve (AUC). Training and validation curves are also shown to investigate the model learning behaviour and to examine for overfitting. Comparative and subject-wise assessments carried out to investigate the effectiveness and generalization of the proposed models for different levels of cognitive workload. The results and discussion sections describe the results that have been achieved using the VR-EEG framework that has been developed. The performance of the proposed deep learning models is analysed across the different workload levels. The results are analysed in terms of quantitative performances, confusion matrices, training and validation behaviour, ROC curves and, subject-wise analysis. The comparison results give insights into the success of the proposed architectures in the distinction of various cognitive workload levels in an immersive memory-based tasks.

The final part of the thesis is a restatement of the key results and contributions of the research. The proposed system is implemented and proved to be feasible to realize VR-EEG-DL in Gamified cognitive workload assessment system. The study offers insights on how to analyze brain activity in a VR immersive cognitive task and shows the potential of using intelligent VR-EEG for an objective workload assessment. Also, the limitations and future research are highlighted in the thesis. Future versions and enhancements may include larger data sets with more diverse types of data, increased user generalizability of the model, more advanced EEG processing algorithms, a broader range of VR supported cognitive tasks, and real-time assessment of the cognitive workload. Overall, the research is part of the ongoing development of integrated VR-EEG framework for gamified cognitive workload assessment. The proposed system combines Virtual Reality tasks, brain activity monitoring based on EEG, and classification based on deep learning, which will serve as a foundation for developing a system of intelligent, objective and interactive cognitive assessments.