EEG Based Classification of a Video Gaming task with 1D Signal VS 2D Image using Machine Learning & Deep Learning techniques

Thesis submitted to the SASTRA Deemed to be University
in partial fulfillment of the requirements
for the award of the degree of

B. Tech. Electronics & Communication Engineering

Submitted by

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This is to certify that the thesis titled **"EEG Based Classification of a Video Gaming task with 1D Signal VS 2D Image using ML & DL techniques"** submitted in partial fulfillment of the requirements for the award of the degree of B. Tech. Electronics & Communication Engineering to the SASTRA Deemed to be University, is a bona-fide record of the work done by **Kavinesan P (Reg. No.: 225004034) Nithish Kumar D (Reg. No.: 225004054) Srivatchaw S U (Reg. No.: 225004080)** during the final semester of the academic year 2024-25, in the **SRINIVASA RAMANUJAN CENTER**, under my supervision. This thesis has not formed the basis for the award of any degree, diploma, associateship, fellowship or other similar title to any candidate of any University.

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Name with Affiliation :

Date :

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Declaration

I/We declare that the thesis titled **"EEG Based Classification of a Video Gaming task with 1D Signal VS 2D Image using ML & DL techniques"** submitted by me/us is an original work done by me/us under the guidance of **Dr V. G. Rajendran, Asst. Professor-III, Department of Electronics & Communication Engineering, Srinivasa Ramanujan Centre** during the final semester of the academic year 2024-25, in the **Srinivasa Ramanujan Centre**. The work is original and wherever I/We have used materials from other sources, I/We have given due credit and cited them in the text of the thesis. This thesis has not formed the basis for the award of any degree, diploma, associate-ship, fellowship or other similar title to any candidate of any University.

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Abstract

This project focuses on classifying video gaming tasks using EEG (Electroencephalogram) signals recorded while participants perform two types of games: a shooting game and a puzzle-solving task. The goal is to identify whether the player is a novice (0) or an expert (1) based on their brain signal patterns. Both Machine Learning and Deep Learning models are developed for this purpose. EEG signals are processed and analyzed in two formats: 1D raw signals and 2D scalogram images. The 1D signals are used for both Machine Learning and Deep Learning models, while the 2D scalogram images are analyzed using Deep Learning models such as CNN and BLSTM. The performance of each model is evaluated using both types of data. Although different approaches are used—1D signal analysis with Machine Learning and Deep Learning, and 2D scalogram analysis with Deep Learning—the results show that the classification accuracy is almost the same. This highlights that both signal processing methods produce similar performance.

Specific Contribution

I assisted in collecting raw EEG data for both Sudoku and Call of Duty (COD) tasks. For 1D processing, I used the feature-extracted data to perform deep learning. For 2D processing, I used scalogram images to carry out deep learning classification.

Specific Learning

Through this process, I learned to work with EEG data, including pre-processing, feature extraction, and preparing both 1D and 2D inputs—like feature matrices and scalogram images—for deep learning models such as CNN and BiLSTM.

Technical Limitations & Ethical Challenges faced

Technical limitations included EEG signal noise, limited data for deep learning, and inter-subject variability affecting model accuracy. **Ethical challenges** involved ensuring informed consent, data privacy, and avoiding misinterpretation of mental states.

Keywords: *EEG signal classification, Brain-Computer Interface (BCI), Deep learning, Scalogram, Cognitive state detection.*

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Abstract

This project focuses on classifying video gaming tasks using EEG (Electroencephalogram) signals recorded while participants perform two types of games: a shooting game and a puzzle-solving task. The goal is to identify whether the player is a novice (0) or an expert (1) based on their brain signal patterns. Both Machine Learning and Deep Learning models are developed for this purpose. EEG signals are processed and analyzed in two formats: 1D raw signals and 2D scalogram images. The 1D signals are used for both Machine Learning and Deep Learning models, while the 2D scalogram images are analyzed using Deep Learning models such as CNN and BLSTM. The performance of each model is evaluated using both types of data. Although different approaches are used—1D signal analysis with Machine Learning and Deep Learning, and 2D scalogram analysis with Deep Learning—the results show that the classification accuracy is almost the same. This highlights that both signal processing methods produce similar performance.

Specific Contribution

For the Call of Duty (COD) task, I collected raw EEG data, extracted features for 1D processing, and applied machine learning for classification. For 2D processing, I generated scalogram images and arranged them as input for deep learning models.

Specific Learning

This process helped me develop a strong understanding of EEG data handling—from pre-processing and feature engineering to structuring datasets for effective integration with machine learning and deep learning frameworks in the context of brain-computer interfaces**.**

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LIST OF ALGORITHMS

ABBREVIATIONS

EEG	Electroencephalogram
COD	Call of Duty
SUDO	Sudoku
PSYTASK	Psychophysiology Task
KNN	K-Nearest Neighbors
SVM	Support Vector Machine
MMSE	Mini-Mental State Examination
ESRB	Entertainment Software Rating Board
IIR	Infinite Impulse Response
LSD	Least Significant Difference
ROC	Receiver Operating Characteristics
AUC	Area under the ROC Curve
SAM	Self-Assessment Manikin
LF	Low Frequency
HF	High frequency
CNS	Central Nervous System

CHAPTER 1
INTRODUCTION

By April 2025, gaming is the world's most popular activity, with 3.4 billion people estimated to be gamers on the planet. Asia arms inflates with 1.6 billion+ players and Europe trails in second with ~750 million gamers. The gaming population in India is expected to grow from 507 million in 2021 to 700 million in 2025. This boom is attributed to the growing penetration of smartphones, cheap internet access, and rising interest in mobile and online gaming. Not only do we play different kinds of games, from sports and boardgames to videogames and puzzles, for fun and relaxation, but we do it to interact with each other too. Aside entertainment, games help in building problem-solving, strategic, team work, and planning skills. Games have been a fundamental aspect of human culture for centuries and are still effective tools for learning, engagement, and meeting others.

The title of this project is "EEG Based Classification of a Video Gaming Task with 1D Signal vs 2D Image using Machine Learning & Deep Learning Techniques". It involves studying EEG signals captured while an individual is engaged in a video game. The brain signals are analyzed in both forms: as raw 1D signals and as images of 2D scalograms. For the purpose of classifying the data, deep learning architectures such as Convolutional Neural Network (CNN) for the 2D images and Bidirectional Long Short-Term Memory (BiLSTM) for the 1D signals are employed. The objective is primarily to classify the gamers into two groups novice and expert depending on their brain activity. This assists in comprehending the way the brain responds during gaming and aids in research on brain-computer interfaces and assessment of cognitive skills.

1.1 TYPES OF GAMES

Games are activities that people play for fun, to relax, or to improve their skills. There are different types of games, and each type gives a different kind of experience. Physical games like cricket, football, and running involve body movement and are usually played outdoors. Board games such as chess, ludo, and snakes and ladders are played indoors and help improve thinking, planning, and decision-making.

Today, video games are one of the most popular types of games. They are played on mobile phones, computers, and gaming consoles. Video games are divided into different genres like action games (fast and exciting), adventure games (with stories and missions), puzzle games (which test thinking skills), simulation games (which copy real-life activities like driving or farming), sports games, and strategy games. Some video games also allow multiplayer mode, where people from different places play together online. Each type of game is enjoyed by different people and age groups. Fig 1.1 illustrates the various categories of games and highlights the diversity in how they are played and what skills they develop. Besides entertainment, games also help improve focus, memory, coordination, and learning, and are now used in research and training as well.

(A)

(B)

(C)

(D)

Fig 1.1: Types of games (A) Board Games (B) Card Games (C) Video Games (D) Sports Games

1.2 VIDEO GAMES FOR HUMANS

Video games provide more than entertainment they have numerous advantages for humans by challenging the mind and enhancing skills. Action games, for instance, improve reflexes, hand-eye coordination, and fast decision-making since they demand rapid responses and concentration. Puzzle games such as Sudoku, challenge problem-solving skills, enhance memory, and enhance critical thinking.

Adventure and role-playing games (RPGs) foster creativity and narrative by engaging players in intricate stories. They prompt players to be strategic and make choices that influence the direction of the story. Sports games, however, assist players in exercising teamwork, strategic thinking, and focus by simulating actual sporting situations.

In addition to cognitive skills, video games can also help in mental wellness. They serve as an outlet, reducing tension, anxiety, and depression in a fun experience. Video games also promote interaction, especially under multiplayer, in which players have the ability to create communities and friendships.

Video games are not just entertainment but also a strong tool to enhance brain functions, aid in relaxation, and encourage social relationships. [1]

1.3 BENEFITS OF VIDEO GAMES

Video games have numerous advantages over mere entertainment. They can enhance cognitive abilities such as problem-solving, memory, and rapid decision-making. Strategy and planning games like puzzle games or action games enable players to think critically and respond rapidly. Video games can also improve hand-eye coordination and concentration, which makes them valuable tools for mental stimulation. Most games are engineered to be challenging, holding a player's brain active and sharpening focus. Certain games offer educational enrichment too, which can teach an individual skills pertaining to mathematics, languages, or history while they're enjoying fun as well as interaction.

Outside cognitive advantages, video games even extend to affect a person emotionally. Playing games is one of the best ways to chill and destress, since it enables people to forget daily stresses and lose themselves in alternate universes. Multiplayer games offer a stage on which people come together to cooperate, build friendship, and network, something especially beneficial to persons who are active online. Moreover, certain games are employed in healthcare environments for physical and mental healthcare, which provides advantages such as lowering stress and encouraging physical activity. Thus, the Fig 1.2 says video games have considerable importance in both personal growth and social interaction.

Fig 1.2: Benefits of Playing Video Games

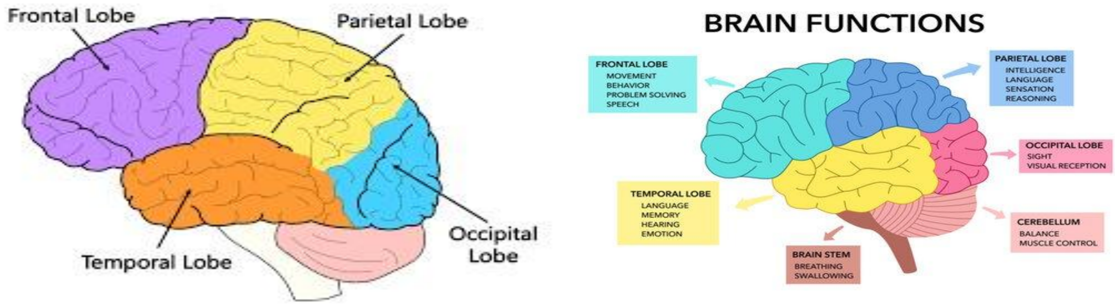
1.4 HUMAN MEMORY DURING GAMEPLAY:

1.4.1 Human Brain

The human brain is an extremely powerful and complex organ that governs all the bodily functions such as thoughts, feelings, movements, and essential life processes. The brain consists of approximately 86 billion neurons that transmit and receive signals to and from the various parts of the body. The brain is divided into various sections, each of which has a specific function. The cerebrum is the largest component and is further subdivided into four lobes: the frontal lobe, which is concerned with decision-making, solving problems, and voluntary movements; the parietal lobe, which receives sensory information such as touch and sense of place; the occipital lobe, which processes sight; and the temporal lobe, which is concerned with hearing, memory, and the interpretation of language. Fig 1.3 provides a visual overview of these divisions and their respective roles, aiding in the understanding of how different brain regions contribute to human cognition and perception. [3]

Aside from the cerebrum, there are two other essential components of the brain, namely the cerebellum and the brainstem. The cerebellum is found beneath the cerebrum towards the rear end of the brain, and is largely in charge of balance, coordination, and dexterity. It assists in ensuring that our actions are smooth and precise. The brainstem links the brain to the spinal cord and regulates fundamental life-supporting functions like breathing, heart rate, and digestion. It serves as a relay station, relaying messages from the brain to the rest of the body.

All these components of the brain, together, function in harmony to keep us alive, conscious, and capable of interacting with the world around us.



(A) **(B)**

Fig 1.3: Anatomy of Human brain: (A) Lobes of brain (B) Functions of each lobe

1.4.2 Human Memory

Human memory refers to the brain's capacity to store, retain, and remember information when required. It is a very crucial part of our everyday life, assisting us in remembering names, locations, experiences, skills, and feelings. Memory helps us learn from the past, make choices, and even shape our personality. Without memory, we would not be able to identify people, maintain routines, or even communicate effectively.

Memory is generally categorized into three broad categories: sensory memory, short-term memory, and long-term memory. Sensory memory stores information from our senses (such as sights or sounds) for a few seconds. Short-term memory stores small pieces of information for a short period (such as remembering a phone number for a few seconds). Long-term memory retains information for an extended period — even a lifetime — and contains facts, experiences, and acquired skills. The hippocampus, which is a brain component found in the temporal lobe, has a significant function in creating and structuring new memories. Memories are retained throughout various regions of the brain, particularly the cerebral cortex, over the long term. Memory is not infallible; it can be lost or altered with time, but through practice and learning, we can improve and reinforce it. Fig 1.4 visually summarizes this process, illustrating how information flows through the different types of memory and highlighting the key brain regions involved in memory formation and retention. [2]

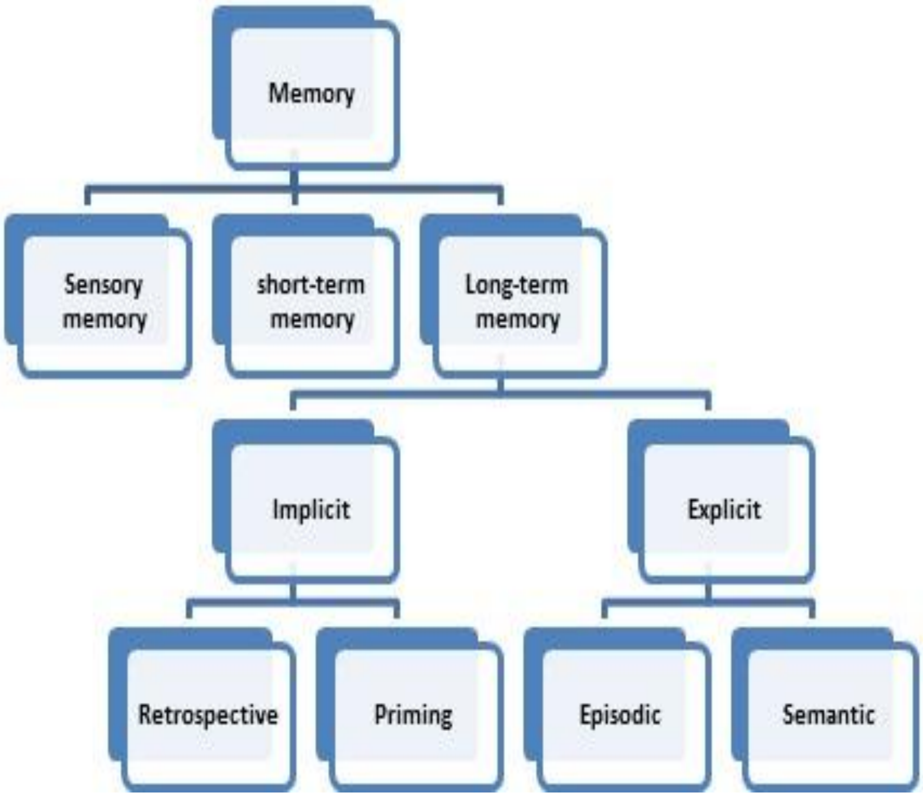


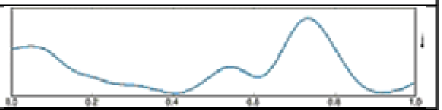
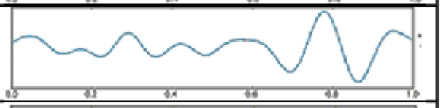
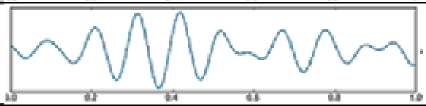
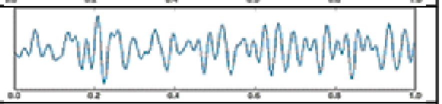
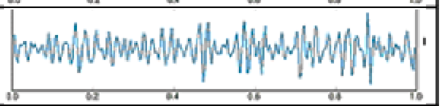
Fig 1.4: Flow chart of Memory

1.5 ELECTROENCEPHALOGRAPH

Electroencephalography (EEG) is a non-invasive method used to measure the brain's electrical activity through sensors placed on the scalp. It records brainwaves, which are patterns of electrical signals generated by neurons. These brainwaves vary in frequency and are closely linked to different mental and emotional states. By analyzing these signals, EEG helps in understanding brain function, diagnosing sleep disorders, and studying attention, stress, and relaxation levels.

Table 1.1**:** Frequency bands of EEG Signal illustrates five main EEG frequency bands: Delta (0–4 Hz), Theta (4–7 Hz), Alpha (8–12 Hz), Beta (12–30 Hz), and Gamma (above 30 Hz). Each band is associated with a specific state of mind. Delta waves appear during deep sleep, while Theta waves indicate drowsiness or light sleep. Alpha waves are seen in relaxed but awake states. Beta waves reflect active thinking and focus, and Gamma waves are linked to high-level cognition or stress. The figure also includes filtered waveforms for each band, showing how their patterns differ in shape and speed, helping to visually distinguish each brain state. [4]

Table 1.1: Frequency bands of EEG Signal

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	

The Fig 1.5 EEG electrode placement conforms to the 10/20 system, a standardized procedure adopted in neurophysiology to locate electrodes on the scalp for electroencephalography (EEG). This is derived from the relative distances between the anatomical landmarks of the head—nasion, inion, and preauricular points—with electrodes positioned at 10% or 20% along these distances. Electrodes are named by the brain area they cover: F (frontal), T (temporal), C (central), P (parietal), O (occipital), and Z (midline), with numbers (odd for the left hemisphere, even for the right). This methodical arrangement provides reproducible and consistent measurements across subjects, allowing precise monitoring of brain activity for research and clinical diagnosis.

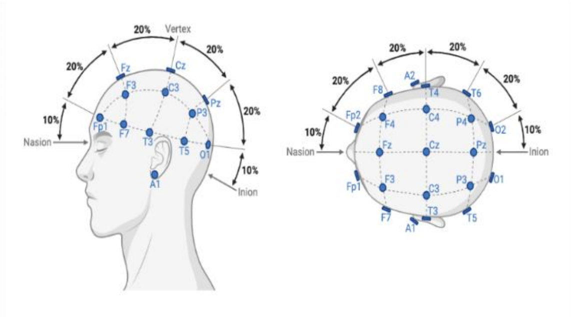


Fig 1.5: 10-20 system of electrode placement

CHAPTER 2
LITERATURE REVIEW

2.1 LITERATURE SURVEY

Table 2.1: Literature surveys

Title	Author	Name of the Journal & Year of Publication	Physiological Parameter used (features extracted)	Classifier and Accuracy	Inference
A 2D-CNN-Scalogram based Approach to Classify the Mental Tasks using EEG Signals	Anuradha Chaudhary, Aruna Tyagi	ICICCS 2022 (International Conference on Intelligent Computing and Control Systems)	EEG signals (brainwaves) Time-frequency image (scalograms) generated using CWT	CNN - 87.48%	Its improved performance for Brain-Computer Interfaces and mental health task through enhanced time-frequency feature extraction
EEG-Based Mental State Classification Using Wavelet Packet Decomposition	V. G. Rajendran, S. Jayalalitha, K. Adalarasu, R.Mathi	Multimedia Tools and Techniques 2024	EEG signals Wavelet Packet Decomposition (WPD) for sub-band energies (Theta, Alpha, Beta)	Cubic SVM - 89.74%	Stress classification using WPD and cubic SVM is effective for early stress detection and cognitive monitoring in BCIs
Classification of Dementia EEG Signals by Using Time-Frequency Images for Deep Learning	Sena Yagmur Sen, Ozlem Karabiber Cura, Aydin Akan	Innovations in Intelligent Systems and Applications Conference (ASYU) 2023	EEG signals Intrinsic time scale Decomposition (ITD), Short-Time Fourier Transform (STFT)	2D CNN - 89.20%	ITD enhances EEG spectrogram classification, boosting CNN accuracy, making it effective for early Alzheimer's Dementia detection
Cognitive stress Recognition During Mathematical Task and EEG changes following Audio-Visual Stimuli for Relaxation	Rashmi C R, Dr. Shantala C P	International Conference on Sustainable Communication Networks and Application 2023	Emobio-8 device Multi-wavelet transformation using Daubechies 14 wavelet	LSTM - 86%	EEG signals showed increased beta power in stress and alpha in relaxation; LSTM classified states with 86% accuracy, enabling stress detection
Classification of EEG Learning and Resting states using 1D-Convolutional Neural Network for Cognitive Load Assessment	A. Qayyum, M. A. Khan, M. Mazher, M. Suresh	2018 IEEE student conference on Reasearch and Development	EEG signals to differentiate between learning and resting states	CNN - 98.75%	The study high accuracy suggests 1D-CNNs effectively classify EEG-based cognitive states, benefiting real-time cognitive load assessment and adaptive learning
A Statistical Analysis on Learning and Non-Learning Mental States Using EEG	Moona Mazher, Aamir Saeed Malik, Abdul Qayyum	2015 IEEE student Conference on Reasearch and Development	Power spectral density features derived from delta, theta, alpha and beta brain waves using FFT and DWT	Not defined accuracy	The study reveals EEG patterns differences in learning states, aiding cognitive load research and brain-computer interface development for mental state analysis
An Investigation of the Multi-Dimensional (1D vs. 2D vs. 3D) Analyses of EEG signals using Traditional Methods and Deep Learning-Based Methods	Darshil Shah, Gopika Gopan K, Neelam Sinha	Frontiers in Signal Processing 2022	EEG signal using Differential entropy, Hurst exponent, Hjorth parameters (activity, mobility, complexity)	1D: Random Forest, SVM, k-NN, AdaBoost - 88.51%; 2D: CNN with Feature Pyramid Network and Atrous Spatial Pyramid Pooling - 76.6%; 3D: Achieved highest accuracy -92.5% for EEG baseline, 98.81% for mental arithmetic	3D EEG analysis is best for cognitive tasks, 1D features suit Parkinson's detection and 2D helps with emotion classification efficiently

In this project, a detailed literature survey was conducted to understand existing research related to EEG signal processing, cognitive task classification, and gaming-related brain activity analysis. The selected references provide foundational insights into both machine learning and deep learning approaches used for EEG-based classification. These works explore various signal processing techniques, feature extraction methods, and model architectures that have been proven effective in cognitive load detection, mental task classification, and neurofeedback systems.

The cited papers highlight the effectiveness of using EEG signals to differentiate mental states under different tasks such as gaming, memory work, and attention-based activities. Some studies emphasize the significance of specific brain regions and EEG channels, while others demonstrate the role of convolutional neural networks and time–frequency analysis (e.g., wavelet transforms and scalograms) in improving classification accuracy. These references were critical in shaping the methodology of this project, including the decision to use scalogram images and deep learning for classifying gaming tasks such as Sudoku and Call of Duty.

2.2 SELF-ASSESSMENT QUESTIONNAIRE

Self-report questionnaires are common research tools in psychology and cognition to assess the emotional and mental well-being of an individual. These questionnaires generally take the form of structured questionnaires where respondents score their feelings, stress, concentration, or mood on Likert scales or fixed options. Though easy to use, they rely greatly on the self-concept of the participant, their honesty, and their comprehension of the questions, which can add subjectivity and bias. In the context of mental health, stress detection, and assessment of cognitive load, these questionnaires are used as a preliminary diagnostic tool or additional measure. Nonetheless, in recent literature, researchers are shifting toward more objective measurements because of the limitations of self-reports. The research in the table illustrates an increasing trend from exclusive questionnaire-based evaluation towards machine learning models based on EEG signals, since they offer real-time, measurable, and unbiased information about brain activity. This is a sign of the necessity to complement or cross-validate self-assessment questionnaires with physiological signal analysis to enhance reliability and accuracy.

2.3 USING PHYSIOLOGICAL SIGNALS

Physiological signals, especially EEG (electroencephalogram), are crucial for decoding mental processes and emotional states through providing real-time, high-resolution information about brain activity. The reviewed literature indicates the application of EEG signals in various fields including stress detection, cognitive load estimation, dementia diagnosis, and learning/resting state classification. EEG records electrical activity from the brain that is subsequently analysed employing techniques such as Wavelet Packet Decomposition (WPD), Short-Time Fourier Transform (STFT), and Intrinsic Time Scale Decomposition (ITD) in order to obtain frequency-based features including alpha, beta, theta, and delta waves. These features indicate different states of mind — for example, beta activity is associated with stress and alertness, and alpha waves with relaxation. Classifiers like CNNs, LSTMs, and SVMs have demonstrated high accuracy in classifying these states with some research exceeding 98% accuracy. Physiological signal integration allows for more objective and accurate mental state classification with less reliance on subjective techniques like self-reporting. [5]

2.4 IMAGING TECHNIQUES

Imaging methods in EEG-based research mainly encompass transforming time-series signals into visual representations that are more interpretable to deep learning algorithms. The literature confirms the application of scalograms, spectrograms, and time-frequency images derived using CWT, STFT, and ITD. These methods translate 1D EEG data into 2D or even 3D images that encompass detailed temporal and spectral patterns affiliated with mental states. These representations enable convolutional neural networks (CNNs) to learn spatial relationships effectively and glean meaningful features. For instance, the use of the 2D-CNN model based on scalogram recorded an accuracy of 87.48% in labeling mental tasks, while other methods utilizing 3D feature representation took the accuracy to an almost 98.81% for arithmetic tasks. These imaging methods not only improve the classification performance but also deliver a visual perception of EEG patterns, rendering them appropriate for clinical interpretation and real-time usage in Brain-Computer Interfaces (BCIs).

2.5 RESEARCH GAP

In spite of remarkable progress in EEG-based mental state classification, there are still some gaps in research. First, the majority of studies emphasize controlled settings with particular tasks such as math problem-solving or relaxation, which restricts generalization to naturalistic settings. Second, although deep learning and signal decomposition methods have shown high accuracy, combination with conventional self-assessment techniques is uncommon. Interweaving subjective self-report data with objective imaging and physiological data would improve personalization and interpretability in use cases such as stress tracking and learning assessment. Also, although a majority of research studies investigate 1D and 2D signal/image forms, 3D EEG analysis although more complete still has limited exploitation because of complexity in computation. There are few large, heterogenous datasets as well as real-time deployment settings in these studies. Filling these gaps may lead the way to strong hybrid models that bring together old and new methods, providing scalable and individualized solutions in education, healthcare, and mental health surveillance systems.

CHAPTER 3
OBJECTIVE AND HYPOTHESIS

The primary goal of this study is to classify user expertise—novice or expert—during a video gaming task by analyzing EEG signals using both 1D signal data and 2D scalogram representations. By examining brainwave activity during gameplay, the study aims to identify distinct neural patterns associated with different levels of gaming proficiency. Additionally, this research compares the performance of machine learning techniques on 1D EEG signals with deep learning models applied to 2D scalogram images, in order to determine the most effective approach for expertise classification using EEG data.

3.1 OBJECTIVES:

To collect EEG signals from participants while performing a video gaming task.

- To analysed the EEG signals in both 1D time-series format and 2D scalogram images generated via wavelet transform.
- To classify players into novice and expert categories using machine learning algorithms on 1D EEG data.
- To implement and evaluate deep learning models on 2D scalogram images for the same classification task.
- To compare the performance Metrix of 1D signal-based vs 2D image-based approaches in expertise classification.

3.2 HYPOTHESES:

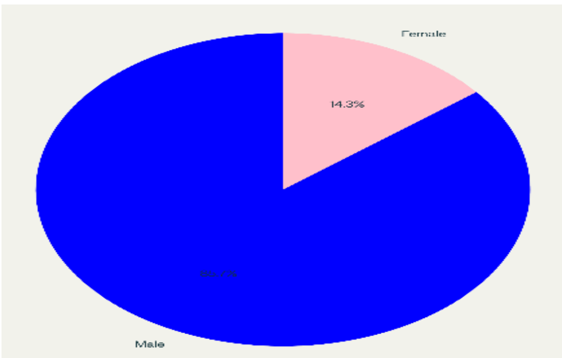
- **H1:** There is a significant difference in EEG activity patterns between novice and expert players during video gameplay.
- **H2:** Deep learning models using 2D scalogram outperform traditional machine learning models using 1D EEG signals in classifying player expertise.
- **H3:** EEG-based analysis can effectively distinguish between levels of gaming expertise, highlighting consistent cognitive and neural differences.

CHAPTER 4

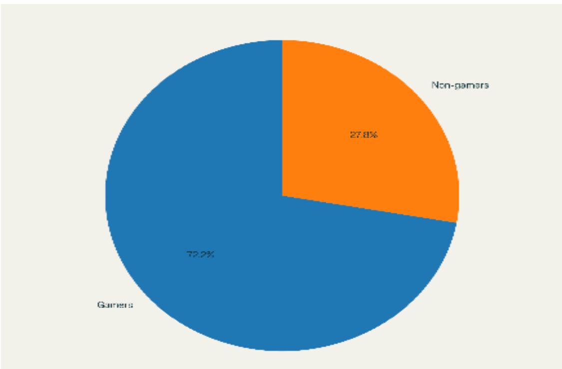
MATERIALS AND METHODS

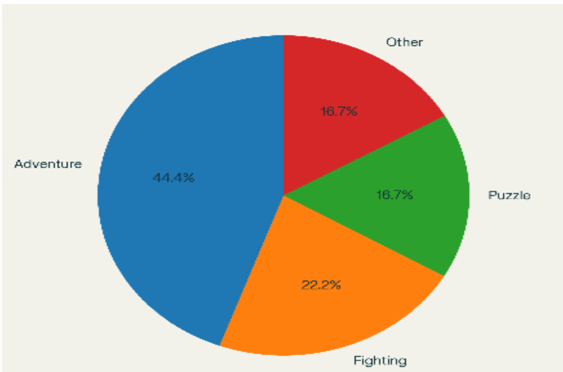
4.1. SUBJECTS SUMMARY:

Fourteen healthy adults (12 males and 2 females) aged 17 to 22 years, with an average height of 1.5 m and an average weight of 68.22 kg, participated in the study. One participant was omitted due to more noise and artifacts. Fig 4.1(A) illustrates the gender distribution among the subjects, with 85.7% males (12 subjects) and 14.3% females (2 subjects). Fig 4.1(B) shows that 72.2% of participants are gamers, while 27.8% are non-gamers. Among the gamers, preferences varied: 44.4% favoured adventure games, 22.2% enjoyed fighting games, 16.7% preferred puzzle games, and another 16.7% chose sports games, as shown in Fig 4.1(C). All procedures followed the guidelines of the Institutional Ethics Committee for Human Volunteer Research at SASTRA Deemed University. Prior to participation, all subjects provided written informed consent. The experiments were conducted at the Simulation Lab/Project Lab, Department of Electronics and Communication Engineering, Srinivasa Ramanujan Centre, Kumbakonam.



(A)





(B) **(C)**

Fig 4.1 Participants: (A) Percentage of gender difference (B) Percentage of gamers (C)Types of games preferred by gamers

4.2 MINI-MENTAL STATE EXAMINATION (MMSE)

The Mini-Mental State Examination (MMSE) also gives a quantifiable score that ranges from 0 to 30, aiding in the categorization of the degree of cognitive functioning among people. As revealed in Table 4.1 a normal score is that which falls within the range 25 to 30, pointing to no meaningful cognitive impairment. Scores between 21 and 24 indicate mild cognitive impairment and may be suggestive of early features of memory loss or decreased mental performance. A score between 10 and 20 suggests moderate impairment, usually accompanied by evident difficulties with daily functioning. Finally, scores less than 10 reflect severe cognitive impairment, usually necessitating constant supervision and assistance. Such classification enables clinical professionals to make informed choices when it comes to diagnosis, treatment, and planning care. [6]

Table 4.1: Scores of cognitive levels

MMSE Score	Cognitive Status	Interpretation
25 – 30	Normal	No significant cognitive impairment
21 – 24	Mild Cognitive Impairment	Possible early-stage cognitive decline
10 – 20	Moderate Cognitive Impairment	Noticeable memory and functional issues
0 – 9	Severe Cognitive Impairment	Serious impairment; needs full-time care

4.3 GAME CHOOSEN

Selecting Call of Duty: Modern Warfare 2 and Sudoku for this EEG-based brain research project provides a rich and diverse examination of human mental processes. Call of Duty: Modern Warfare 2 is an action-packed first-person shooter video game that pushes the brain with quick attention switching, under-pressure decision-making, and emotional involvement. Sudoku, on the contrary, is a peaceful, logic-driven puzzle game that engages areas concerning problem-solving, working memory, and pattern recognition.

By examining EEG signals as participants engage in these two very different games, we can see how the brain reacts to varying cognitive requirements action-oriented vs. strategy thinking. These variations assist in determining how mental workload, attention levels, and expertise differ between game types. In addition, because both games are well known and popular with many different age groups, they assist in creating high participant interest and even more varied data gathering.

4.3.1 SUDOKU

Sudoku is a math-based puzzle video game that requires players to place numbers in a 9x9 grid so that each row, column, and area includes all the numbers from 1 to 9. Unlike action games, Sudoku demands logical reasoning, pattern observation, and problem-solving abilities. The slow and deliberate nature of the game makes it an excellent tool for studying cognitive processes involved in focused attention, working memory, and decision-making. Players must consider multiple possibilities and evaluate the consequences of each move, thereby engaging brain regions associated with planning and executive function. Fig 4.2 shows a typical example of a challenging puzzle that requires deep thought and sustained attention.

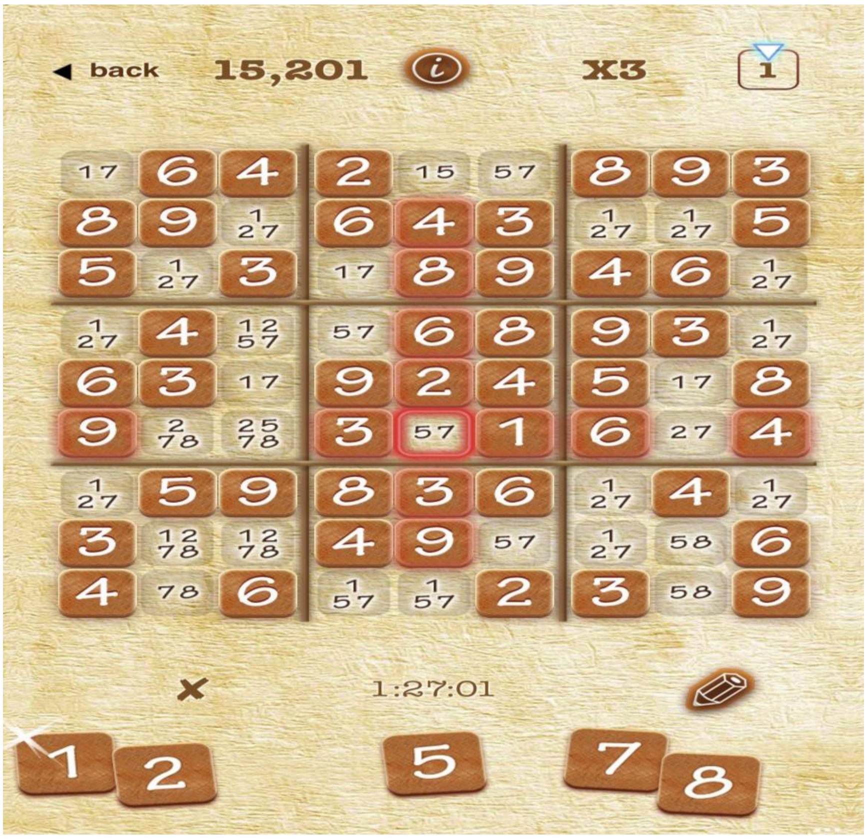


Fig 4.2: A hard level in SUDOKU

From the EEG analysis point of view, playing Sudoku results in heightened brain activity in areas such as the prefrontal cortex, which is vital for higher-order thinking and decision-making. Players often show variations in theta and alpha brain wave patterns, which are associated with relaxation, concentration, and cognitive load during deep mental engagement. The systematic and logical nature of Sudoku stands in sharp contrast to the fast-paced intensity of games like Call of Duty, offering valuable insight into how the brain responds to different cognitive demands. Fig 4.3 displays the completed grid and the time taken, helping researchers associate cognitive performance with gameplay metrics. By analysing brain responses during Sudoku, researchers can better understand the neural mechanisms underlying logical problem-solving, attention, and memory use.

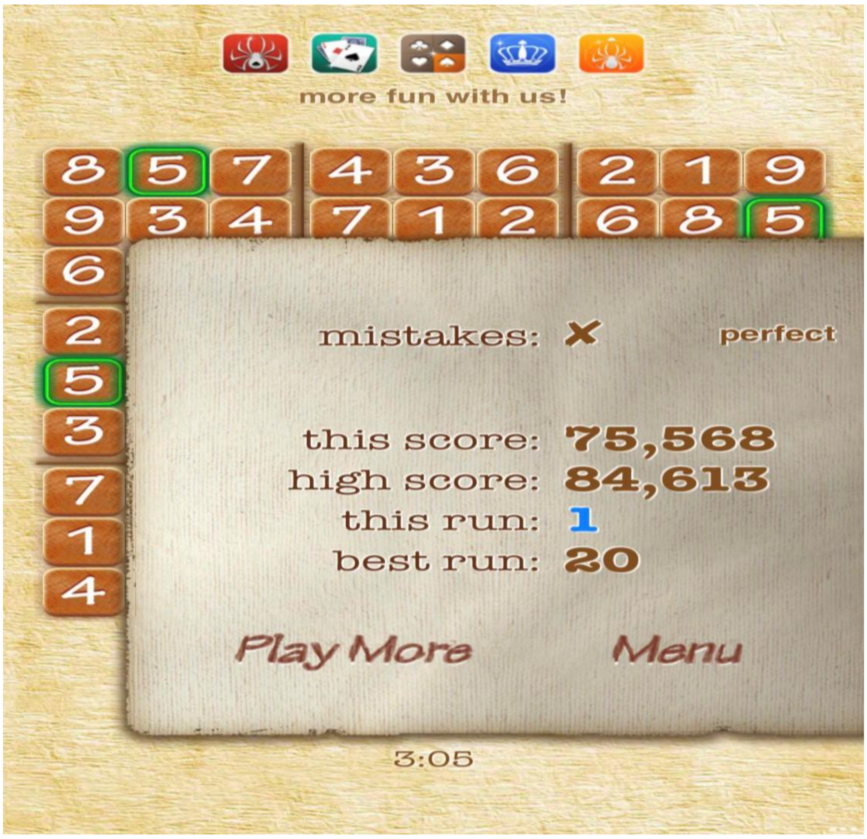


Fig 4.3: Results after finishing a game in SUDO

4.3.2 CALL OF DUTY: MODERN WARFARE 2 (COD MW2)

Call of Duty: Modern Warfare 2 (MW2), released in November 2009, is a first-person shooter developed by Infinity Ward and published by Activision. As the sixth installment in the Call of Duty series and a direct sequel to *Call of Duty 4: Modern Warfare*, the game continues the story of a fictional conflict between global superpowers. Built on the IW 4.0

engine, MW2 pushed the limits of storytelling and immersive gameplay during its time, and it has remained a significant title in both competitive and narrative gaming communities.

MW2 is set in a fictional near-future where international tensions escalate into warfare between Russia and the United States. The game's narrative follows members of the elite multi-national special operations unit, Task Force 141, and U.S. Army Rangers as they respond to terrorist threats and military invasions. Players step into the shoes of multiple characters, including "Soap" MacTavish, a returning protagonist from the previous game, and Private James Ramirez, a U.S. Army Ranger. Fig 4.4 captures the dynamic combat and immersive visuals that define the player experience.

Fig 4.4: Call of duty gameplay

The storyline moves fluidly across global locations such as Afghanistan, Rio de Janeiro, a snowy Russian base, and suburban American neighbourhoods under attack. Each mission adds depth to the plot, involving betrayal, global conspiracies, and a race against time to prevent full-scale world war.

Modern Warfare 2 combines cinematic storytelling with action-packed gameplay. It offers a single-player campaign that features tightly scripted missions filled with intense shootouts, stealth segments, vehicle chases, and large-scale battles. The game encourages strategic thinking, with players often needing to adapt their playstyle based on the situation and available equipment.

The game’s multiplayer mode is one of its most celebrated features, introducing new killstreak rewards, customizable loadouts, and perks that significantly impact player performance. Additionally, MW2 introduced “Spec Ops,” a cooperative mode that allows two players to team up and complete short, objective-based missions across various difficulty levels.

Weapons in the game are based on real-world models and are finely tuned for balance and realism. Players have access to a wide arsenal including assault rifles, sniper rifles, SMGs, explosives, and even tactical gear like heartbeat sensors. Game statistics such as enemies neutralized, completion time, and headshot accuracy are tracked and displayed on a detailed performance summary screen, as seen in Fig 4.5 reinforcing skill development and player engagement.

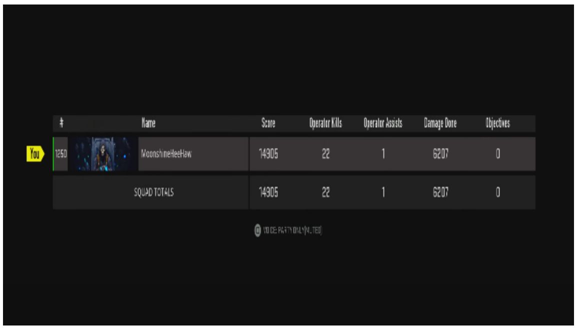


Fig 4.5: Stat screen after finishing a mission in COD

This game is rated *Mature 17+* by the ESRB and *18+* by PEGI due to its intense violence, strong language, and mature themes such as terrorism and warfare. One notable example is the controversial "No Russian" mission, which depicts a terrorist attack and allows players to opt out. Designed for mature audiences, the game includes options to disable explicit content, though the core experience remains serious and intense. Fig 4.6 highlights the rating label that governs the game's accessibility and distribution. Access is generally restricted through age-verification policies enforced by retailers and online platforms, which also moderate gameplay to prevent toxic behaviour such as cheating or harassment. While it lacks advanced accessibility features found in newer games, it offers basic options like subtitle support and aim assist.

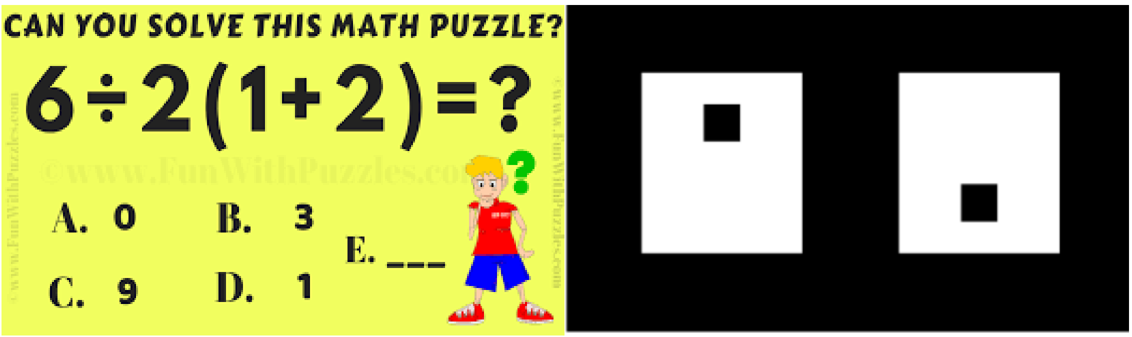
Critically, MW2 was highly praised for its cinematic gameplay and compelling narrative, earning strong reviews from IGN and other major platforms. Despite some controversies, it is widely regarded as a landmark FPS title, with lasting influence that was reinforced by the 2020 remastered campaign release.

Fig 4.6: ESRB Rating sticker provided in a game

4.4 PSYTASK

PSYTASK® is a research programme designed to conduct studies in psychophysics and psychophysiology. Depending on the task, participants should either hit a button or ignore the stimuli that are presented, both visual and auditory. The PSYTASK® software, which provides visual and aural stimuli for psychophysiology experiments, was used to administer the mental task. To assess the subjects' mental performance, a mental arithmetic operation is prompted, and task performance parameters (such as omission and commission mistakes) are recorded in the integrated database as demonstrated.

1. Show participants visual stimuli -TOVA (Fig 4.7 (A))
2. Calculating simple mathematical operation-Addition and Subtraction (Fig 4.7 (B))



(A) **(B)**

Fig 4.7: PYSTASK games: (A) TOVA-Psytask (B) Math-easy-Psytask

One interesting feature of PSYTASK is its ability to give participants mental math problems. Participants might be asked to add, subtract, multiply, or divide. The software tracks their performance and even records how quickly they respond.

- Omission error: Failure to respond to, go trials.
- Commission error: Failure to withhold the response

Here's a key point: the software changes what participants should do based on whether they got the answer right or wrong.

- If they got it right (Go condition), they press a key.
- If they got it wrong (No-Go condition), they stay silent.

This helps researchers see how well people can follow instructions and react differently based on what they see or hear. Overall, PSYTASK provides a structured way to study how our minds and bodies work together. It's a valuable tool for scientists who want to understand human behaviour and thinking.

4.5 SELF-ASSESSMENT QUESTIONNAIRE

Upon finishing a gameplay session, players will be requested to give feedback by responding to ten questions based on the work of Kulshreshth, Arun, and LaViola, Jr. (2013). The questions are intended to assess several aspects of the player's experience, such as effort, time perception, immersion, enjoyment, perceived challenge, performance, emotional connection, appreciation of visual graphics, overall satisfaction, and willingness to play again. The feedback gathered provides useful information regarding player satisfaction and engagement, assisting developers to determine areas for development and improve the general gaming experience.

4.6. EXPERIMENTAL PROTOCOL

4.6.1. EMOTIV EPOC X AND ELECTRODE LOCATIONS

The EMOTIV EPOC X is a high-spec EEG (electroencephalogram) system widely used in brain-computer interface (BCI) applications such as cognitive state monitoring, neurofeedback, and research. The system is particularly valuable in EEG-based brain studies due to its ability to capture real-time brainwave data via 14 active electrodes. It allows researchers to record electrical activity in the brain during various tasks, including learning, gaming, stress management, cognitive workload analysis, and emotional state detection. Fig 4.8 displays the EMOTIV EPOC X headset utilized for data acquisition in this study.

The EMOTIV EPOC X provides excellent data at up to 256 Hz sampling, giving a fine-grained insight into brainwave activity. Its ergonomic shape provides comfort when used over long periods of time, and its wireless feature provides the user with mobility while using it, making it a good fit for both laboratory use and field studies. The system accommodates an array of research and commercial applications and can be used in combination with EMOTIV's software, enabling real-time analysis and visualization of brain activity. It is especially appropriate for studies of cognitive task execution, i.e., video games, emotional reactions, and problem-solving exercises, providing exact answers to how the brain reacts to different cognitive loads.

The EMOTIV EPOC X uses a 14-channel electrode configuration, which is strategically placed across the scalp to capture brainwave signals from different regions. The electrodes are positioned according to the 10-20 International System, which is a widely accepted standard for EEG electrode placement. Here's a breakdown of the electrode locations:

Fig 4.8: Device used in the experiment

- AF3 (Anterior Frontal Left): Located on the left side of the forehead, over the prefrontal cortex.
- F7 (Frontal Left): Placed on the left side of the forehead, slightly above the eyebrow.
- F3 (Frontal Mid Left): Located on the left side of the forehead, over the frontal lobe.
- FC5 (Frontocentral Left): Located on the left side of the head, near the midline of the frontal cortex.
- T7 (Temporal Left): Positioned on the left side of the head, above the ear region.
- P7 (Parietal Left): Placed on the left side of the skull, toward the parietal region.
- O1 (Occipital Left): Located on the left side of the occipital lobe, near the back of the head.
- O2 (Occipital Right): Located on the right side of the occipital lobe, near the back of the head.
- P8 (Parietal Right): Positioned on the right side of the skull, toward the parietal region.
- T8 (Temporal Right): Positioned on the right side of the head, above the ear region.

- FC6 (Frontocentral Right): Positioned on the right side of the head, near the midline of the frontal cortex.
- F4 (Frontal Mid Right): Located on the right side of the forehead, over the frontal lobe.
- F8 (Frontal Right): Positioned on the right side of the forehead, slightly above the eyebrow.
- AF4 (Anterior Frontal Right): Located on the right side of the forehead, over the prefrontal cortex.

Further, electrodes F3 and F4 are associated with attentional processing, while T7 and T8 play roles in short-term memory, speech, musical rhythm, and to some extent, smell recognition. The cerebral cortex, divided into four lobes, is responsible for long-term memory. The electrode positions used in the experiment is shown in Figure 4.10. The colors of the electrode indicate the contact quality of the electrodes.

- GREEN - CONDUCTION AS WELL AS IMPEDANCE IS GOOD
- BLACK - NO CONTACT DETECTED
- RED - CONDUCTION AS WELL AS IMPENDACE IS BAD
- ORANGE - AVERAGE CONTACT QUALITY

The overall electrode placement and contact quality during the experiment are visualized in Fig 4.9 providing a clear representation of signal integrity across the scalp during data collection. [7]

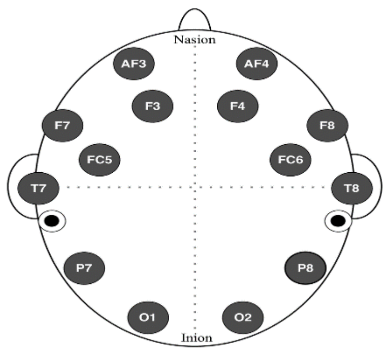


Fig 4.9: Electrode position of EEG headset

4.6.2 EXPERIMENTAL DETAILS

Experimental session for this project is made to have varied phases to note the changes in brain activity in varying conditions. These stages aimed to activate different regions of the brain and elicit distinct patterns in EEG data, enabling the comparison of cognitive loads during calm, strategic, and intense conditions. Fig 4.10 illustrates this sequence and the time duration allocated for each phase of the session. The whole session takes around 21 minutes, and it is separated into the following five stages:

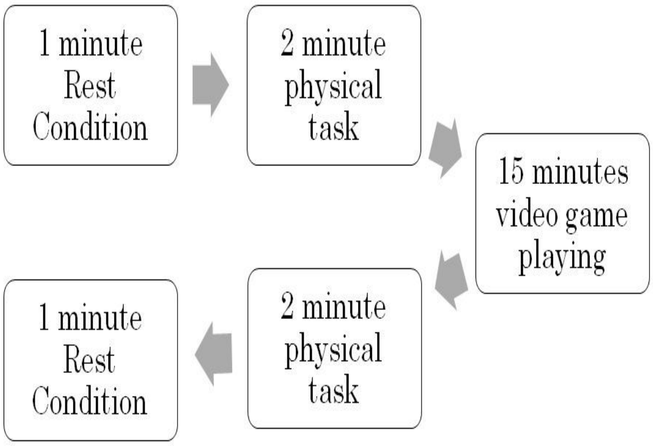


Fig 4.10: Block Diagram of Experimental Protocol

Rest Condition (1 minute):

The session starts with a 1-minute relaxation period. In this period, the subject sits quietly and does not perform any mental or physical operation. This period facilitates recording the baseline EEG signals during relaxation.

Psychological Task (2 minutes):

Following the rest period, the subject completes a psychological task for 2 minutes. This is a task aimed at activating cognitive processes like attention, memory, or decision-making, depending on the task that was employed.

Video Game Play (15 minutes):

The participant then plays a chosen video game for 15 minutes. This is the core part of the experiment, where the EEG signals of the participant are captured while playing actively. This part assists in analyzing the brain response during a high-engagement activity.

Psychological Task (2 minutes):

Post-gameplay, the subject again does the same psychological task for a further 2 minutes. This assists in comparing cognitive activity prior to and after gameplay.

Rest Condition (1 minute):

Lastly, the session concludes with a further 1-minute rest period to capture EEG signals following gameplay and tasks. This assists in determining how the brain returns to a resting state after activity.

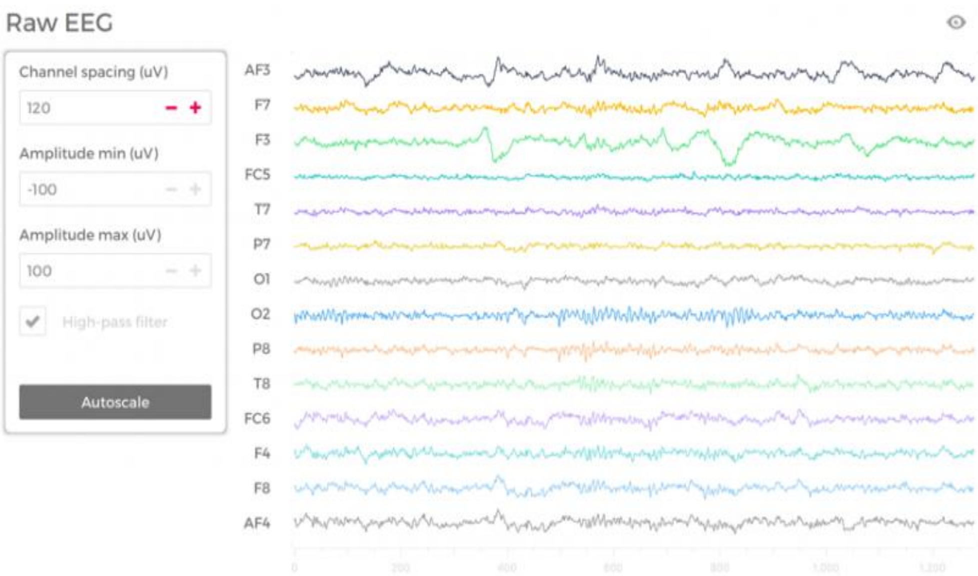


Fig 4.11: Raw EEG Signal Visualization using Emotiv Epoc+ Headset

Fig 4.11 shows the raw EEG signals recorded using the Emotiv Epoc+ headset with 14 electrodes placed at standard scalp locations (e.g., AF3, F7, F3). Each colored line represents brainwave activity from a specific channel, measured in microvolts (µV). The EmotivPRO software visualizes these signals over time, allowing real-time observation of brain activity. This raw EEG data is essential for further analysis like filtering, feature extraction, and classification in BCI applications.

4.7 SIGNAL PROCESSING

The flowchart illustrates the EEG signal processing pipeline designed to classify participants as either experts or novices based on their brain activity while performing cognitive tasks and engaging in video gameplay. The data collection phase begins with EEG signal recording during a series of activities: cognitive tests (such as TOVA and Math tests) are conducted for 2 minutes before and after each gameplay session, which includes 15 minutes of playing Call of Duty and 15 minutes of playing Sudoku, with at least a one-day resting interval between sessions to avoid fatigue and carryover effects.

The recorded EEG signals are then pre-processed using an IIR filter and a 50 Hz notch filter to remove baseline noise and eliminate power line interference. Following this, wavelet decomposition is applied, breaking down the signal into five levels of approximation and detail coefficients, capturing both time-domain and frequency-domain characteristics of the EEG data.

A total of 22 features are extracted from this processed signal, including time-domain features (mean, variance, RMS, skewness, etc.), frequency band powers (delta, theta, alpha, beta, gamma), and non-linear metrics (such as arousal index, entropy, heart rate, and vigilance index). Simultaneously, scalogram — time-frequency images generated from raw EEG signals — are created to serve as inputs for deep learning models.

In the final phase, two parallel classification approaches are implemented: a classic machine learning pipeline that operates on the extracted features, and a deep learning model that uses the scalogram images. Both approaches aim to predict whether a participant is an expert or novice, based on the distinct patterns observed in their brain activity. Fig 4.11 visually represents this entire workflow from data collection to classification.

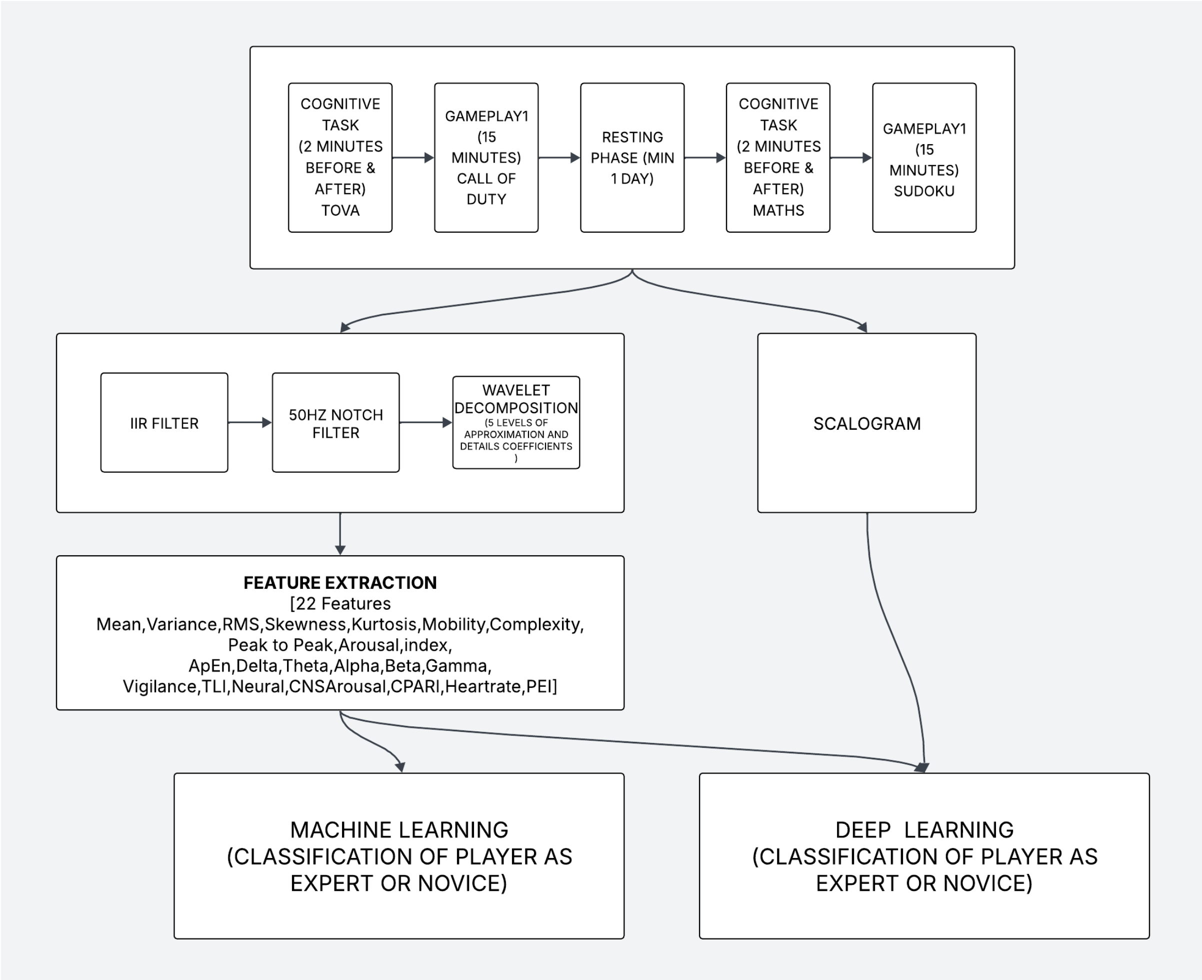


Fig 4.12: Flowchart depicting the signal processing of data

4.8 WAVELET DECOMPOSITION

A signal processing technique known as wavelet decomposition is employed to analyze signals at multiple frequencies and resolutions. The technique works by convolving the signal with wavelet functions, which break the original signal into several components called wavelet coefficients. These coefficients represent the energy of the signal at different levels of detail — higher-level coefficients capture finer, localized changes in the signal, while lower-level coefficients reflect broader, more gradual variations. Fig 4.12 illustrates the steps involved in this process. [9]

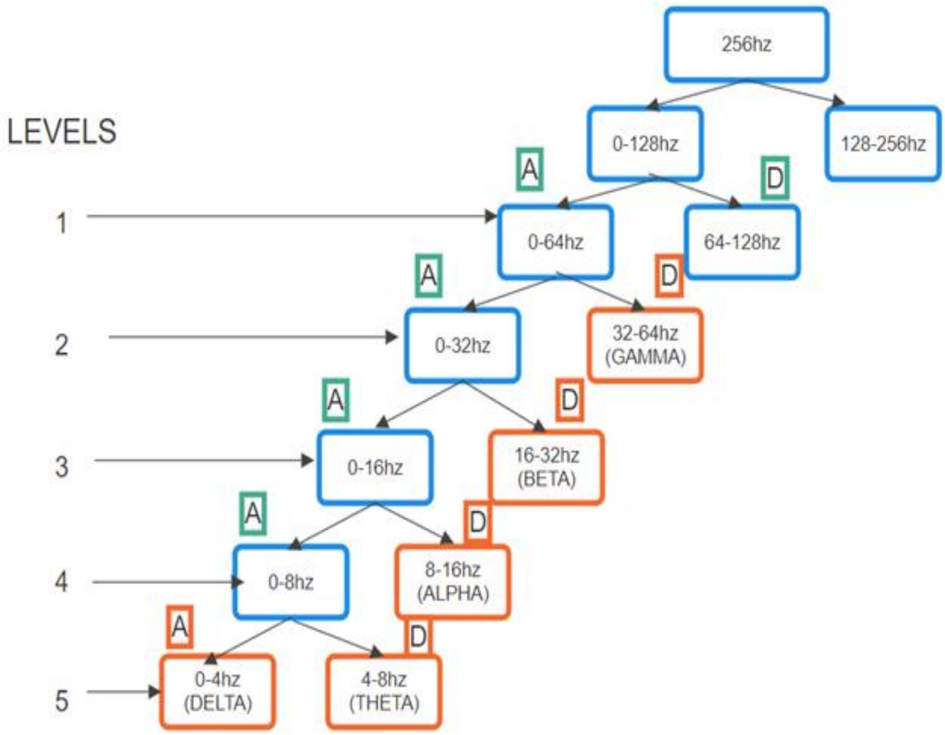


Fig 4.13: Flowchart of Wavelet decomposition method

In this research, wavelet decomposition was applied to the EEG signal using the Daubechies 8 (db8) wavelet function. The decomposition was performed to five levels, yielding detail coefficients (D1-D5) and approximation coefficients (A1-A5). Each of the detail coefficients corresponds to a specific EEG frequency band: delta, theta, alpha, beta, and gamma, each associated with different cognitive and neural functions. The approximate coefficients provide a broader view of the low-frequency trend of the signal.

To reconstruct and analyse the individual frequency bands, the 'wrcoef' function is used. The mean values of the reconstructed coefficients (both A and D) are computed to evaluate the average energy in each band. This helps assess the distribution of brainwave frequencies in the EEG signal, providing valuable insights into cognitive states or mental tasks.

In general, wavelet decomposition enables the extraction of important features from EEG data, which can be applied in neuroscience and cognitive studies. Table 4.2 summarizes the relationship between the brainwave frequency ranges and the wavelet packet decomposition coefficients.

Table 4.2: EEG Bands with their frequency range details and coefficient details

Brainwave	Frequency Range	Wavelet Packet Decomposition Coefficient
Delta	0-4 Hz	A5
Theta	4-8 Hz	D5
Alpha	8-16 Hz	D4
Beta	16-32Hz	D3
Gamma	32-64 Hz	D2

4.9 FEATURE EXTRACTION

Feature extraction is one of the important procedures in EEG signal analysis, wherein useful patterns are extracted from raw, frequently noisy, brainwave signals. During this process, the EEG signal, being continuous, is decomposed initially by employing wavelet transform. This method divides the signal into various frequency bands that align with identified brainwave types: Delta (0–4 Hz), Theta (4–8 Hz), Alpha (8–16 Hz), Beta (16–32 Hz), and Gamma (32–64 Hz). Each of these frequency bands is linked with various cognitive or physiological states—such as deep sleep (Delta), relaxed attention (Alpha), or severe mental processing (Gamma). Following decomposition, the signals are rebuilt for every band through the wrcoef function to isolate and retrieve the original signal shape of every frequency component. This is vital in order to realize how the energy of the EEG signal is distributed across the different brainwave bands.

After reconstructing the frequency band in each case, statistical features such as mean are computed to abstract the average energy of the band over time. They indicate the intensity of particular brainwaves, which can be used to infer cognitive states—such as higher Beta or Gamma activity to show enhanced alertness, common in gamers. Converting raw EEG data to such features makes it easier to compare mental activity between tasks or groups. Table 4.3 consolidates these attributes, which emphasize brainwave differences in tasks such as gaming and puzzle-solving.

Algorithm 4.1: Feature extraction

- **Load EEG Data**: Read the EEG data from the CSV file.
- **Segmentation**: Divide the EEG data into 2-second intervals for ML and 20-second intervals for DL.

- **Wavelet Decomposition**: Apply wavelet decomposition (using 'db4' wavelet) to the EEG signal for each segment.
- **Extract Features**: Extract the detailed coefficients (Gamma, Beta, Alpha, Theta, Delta) from the decomposition.
- **Store Results**: Write the calculated features (Alpha, Beta, Gamma, Theta, Arousal, Vigilance, etc.) into an Excel file.
- **Repeat**: Process the data in multiple channels and repeat the process for each channel.

Table 4.3: Description of feature extracted

Feature	Description	Why It's Extracted
Mean (Central Tendency)	Average of the signal	Understand the signal's central value
Variance (Signal Dispersion)	Represents the average spread of the signal	To assess variability or dispersion
Root Mean Square (RMS)	Square root of mean of squares of signal values	Indicator of signal's overall magnitude
Skewness (Signal Asymmetry)	Quantifies asymmetry of the signal	To understand deviations from normality
Kurtosis (Peak Sharpness)	Measures sharpness of peaks in the signal	Analyse peakedness of signal distribution
Mobility (Signal Variability)	Measures change in signal variation	Analyse variability or restrictions
Complexity (Higher-Order Variability)	Quantifies higher-order variability	To analyses regularity or unpredictability of the signal
Approximate Entropy (Signal Regularity)	Measures signal regularity	To analyses consistency or predictability of signal
Peak-to-Peak Amplitude	Difference between max and min value	To measure signal amplitude range
Total Energy	Total energy across wavelet sub-bands	Quantify overall energy present
Delta Energy (δ)	Energy in delta (δ) band	To assess low-frequency brain activity (deep sleep, attention)
Theta Energy (θ)	Energy in theta (θ) band	To assess drowsiness, meditation, memory tasks
Alpha Energy (α)	Energy in alpha (α) band	To assess calmness, relaxed alertness
Beta Energy (β)	Energy in beta (β) band	To assess focus, cognitive tasks, active thinking
Gamma Energy (γ)	Energy in gamma (γ) band	To assess high-level cognition, learning, memory
Arousal Index	Ratio of alpha to beta energy	Estimate CNS arousal
Vigilance Index	Ratio of alpha + theta to beta energy	Evaluate attentiveness

Task Load Index (TLI)	Ratio of beta to alpha energy	Assess cognitive workload
Neural Activity Index	Ratio of alpha to theta energy	Gauge neural activity
CNS Arousal	Level of central nervous system arousal	Another index of CNS arousal
Heart Rate Estimate	Ratio of alpha to theta energy	Estimate physiological arousal/heart rate
Performance Enhancement Index (PEI)	Ratio of alpha to theta energy	Estimate performance or engagement during tasks

4.10 MACHINE LEARNING

Machine learning is a subfield of artificial intelligence which allows computers to make decisions or predict outcomes from data without programming them explicitly. Machine learning occurs through recognizing patterns in data and applying the patterns to predict the outcome for new, unseen data. Machine learning has found increasing popularity in recent years across fields such as healthcare, neuroscience, and signal processing because it can effectively deal with noisy and complex data.

In this project, machine learning methods are utilized to classify EEG signals according to the extracted features of various brainwave frequency bands. Following wavelet decomposition and feature extraction, a list of statistical features reflecting brain activity is input into several different classifiers in order to test their performance. In particular, five classes of classifiers were utilized: K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Ensemble Classifier, Neural Network, and Decision Tree. Each algorithm learns to distinguish between subjects' cognitive states based on patterns in the EEG data.

The K-Nearest Neighbors (KNN) classifier operates by comparing a test sample with its nearest neighbors in the training set and taking the most frequent class label among them. Support Vector Machine (SVM), however, tries to identify the best hyperplane that maximally separates the classes in a high-dimensional space. The Ensemble classifier pools several weak learners (such as decision trees) to create a more powerful model, enhancing overall accuracy and resilience. Neural Networks draw inspiration from the human brain and are capable of learning intricate nonlinear relationships between input and output, which makes them well-suited to EEG pattern recognition. Finally, the Decision Tree classifier constructs a tree-based model for making decisions based on thresholds of features, providing good interpretability. [10]

Algorithm 4.2: Classification learner

- **Train the models** using five classifiers: SVM, KNN, Decision Tree, Ensemble, and Neural Network.
- **Test the models** on the test dataset.
- **Calculate accuracy** for each model.
- **Print the accuracy** for each model.
- **Identify the best model** based on the highest accuracy.

The performance of every classifier was tested using accuracy measures. This comparison is helpful in recognizing which algorithm is best at reflecting the underlying brainwave patterns for the purpose of classification. The findings are helpful in gaining insights into how well machine learning methods can work for EEG signal analysis, such as separating different subject groups or cognitive states as shown in Fig 4.13.

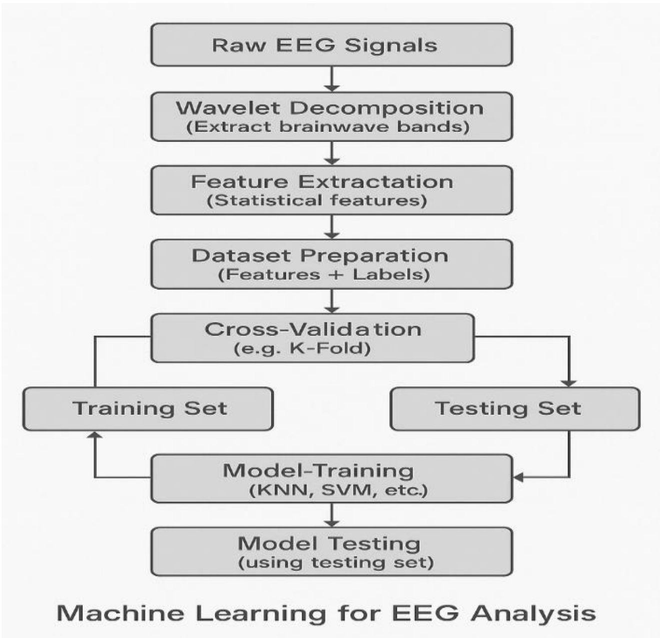


Fig 4.14: Methodology of Machine Learning Technique

4.11 DEEP LEARNING

Deep learning is a subset of machine learning that deals with models of several layers that have the capability to learn sophisticated patterns from raw or pre-processed data. Such models, particularly neural networks with numerous hidden layers, are particularly good at image recognition, sequence modelling, and signal classification tasks. Deep learning works in EEG analysis since it can learn significant features automatically from signals or their visualizations without requiring handcrafted feature extraction.

In this project, deep learning methods are employed to classify EEG signals by processing raw signals as well as their scalogram representations. A scalogram is a time-frequency image created through wavelet transforms, which represents the dynamic changes in brainwave frequencies over time. This makes it suitable to feed into image-based deep learning models such as Convolutional Neural Networks (CNNs).

CNNs are robust models that are widely applied to image classification tasks. They can identify spatial patterns and structures in the images of scalogram to assist the model in making distinctions between distinct cognitive states or subject groups. In addition to CNNs, a Bidirectional Long Short-Term Memory (BLSTM) network is applied. BLSTM is a form of Recurrent Neural Network (RNN) that can discover long-term patterns in time-series data by handling it in the forward and backward directions. This renders BLSTM particularly suited to capturing temporal patterns in unprocessed EEG signals.

By utilizing both CNN and BLSTM models, the system is able to gain both spatial and temporal feature learning. The deep learning models are trained and tested over labeled data, and their performance is assessed over accuracy and other criteria. This methodology provides a more automated and possibly more accurate solution than traditional machine learning, particularly when utilized over large and complicated EEG datasets as shown in Fig 4.14.[11]

Algorithm 4.3: Deep learning

- **Import Libraries:** Import necessary libraries like TensorFlow, NumPy, Matplotlib, etc.
- **Load Dataset**
  - Set the path to scalogram image datasets.
  - Use Image Data Generator to load training and validation datasets.

- **Pre-process Images**
    - Resize all images to a fixed size (e.g., 224x224).
    - Normalize the pixel values.
- **Build CNN Model**
    - Add convolutional layers to extract features.
    - Add max-pooling layers to reduce spatial size.
    - Add dense (fully connected) layers.
    - Use SoftMax activation for final classification.
- **Compile Model**
    - Use categorical cross entropy as the loss function.
    - Use Adam optimizer.
    - Track accuracy as the evaluation metric.
- **Train the Model**
    - Fit the model on the training data.
    - Validate the model on the validation data.
    - Store the training history.
- **Evaluate the Model**
    - Plot accuracy and loss graphs for training and validation.
    - Evaluate model performance on the validation set.
- **Save the Model** (if included)
    - Optionally, save the trained model for future use.

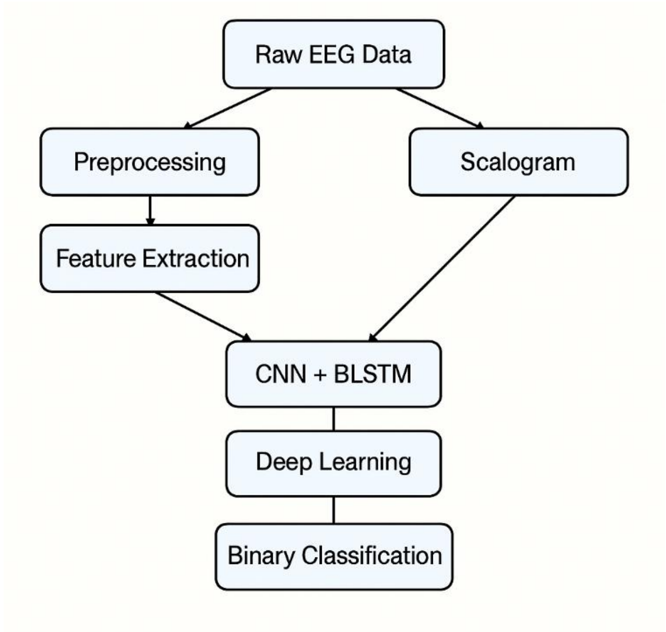


Fig 4.15: Methodology of Deep Learning Technique

4.12 STATISTICAL ANALYSIS

As the data was not normally distributed, the Friedman test (a non-parametric equivalent to repeated measures ANOVA) was applied to compare relative EEG energies (alpha, beta, gamma, theta) in two conditions: gameplay vs. gameplay within, at 14 electrode sites. Participants were separated into novice and expert groups. The test sought to investigate how emotional brain activity changed throughout play. A p-value of 0.05 was applied to test for significance. Where important, post-hoc LSD tests were used for comparisons between pairs. All analyses were conducted using IBM SPSS Statistics v20.

CHAPTER 5
RESULT

5.1 MINI MENTAL TEST RESULT

We tested the mental ability of the subjects through a short mental test before the experiment. As stated earlier, subjects whose MMSE score was less than 25 were excluded from the experiment. Only those with a score higher than 25 were deemed fit to join the experiment. All 14 subject-pairs selected were above this minimum threshold, and none had any sign of cognitive impairment. In addition, the test scores indicate a uniform level of mental alertness among all recruited participants, as shown in Fig 5.1.

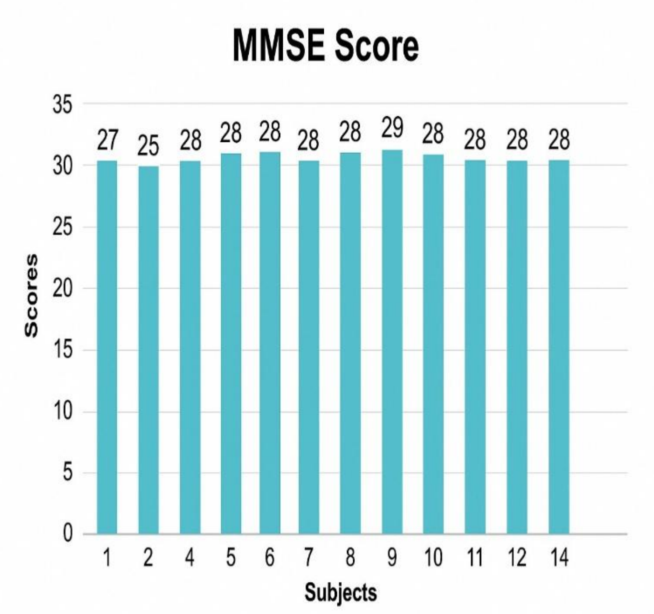


Fig 5.1: Mini mental test scores of subjects

5.2 EXPERT AND NOVICE SEPARATION

The subjects engaged in two distinct video game genres. Sudoku is a puzzle game, whereas Call of Duty is a fighting game. In Call of Duty, the number of enemy kills and respawn status were used to determine the score. In order to finish the objective, the player must eliminate every enemy target. Statistics like opponents vanquished, task completion times, difficulty, and civilian deaths may be tracked by the game. We divided the players into expert and novice categories based on their scores. The average of the scores was used to determine a threshold value. According to our assumptions, a player is classified as an expert if they have killed more than 79 enemies and their respawn status is less than 10, while the rest of the players are classified as novices. Fig 5.2 represents the expertise level of players in Call of Duty.

$$\textbf{Threshold} = \mathbf{1/n^* \ \Sigma \ (s1+s2+s3+\ldots)}$$

n – Total no. of. subjects

s – Scores of subjects

Where:

n – Total number of subjects

s – Scores of subjects

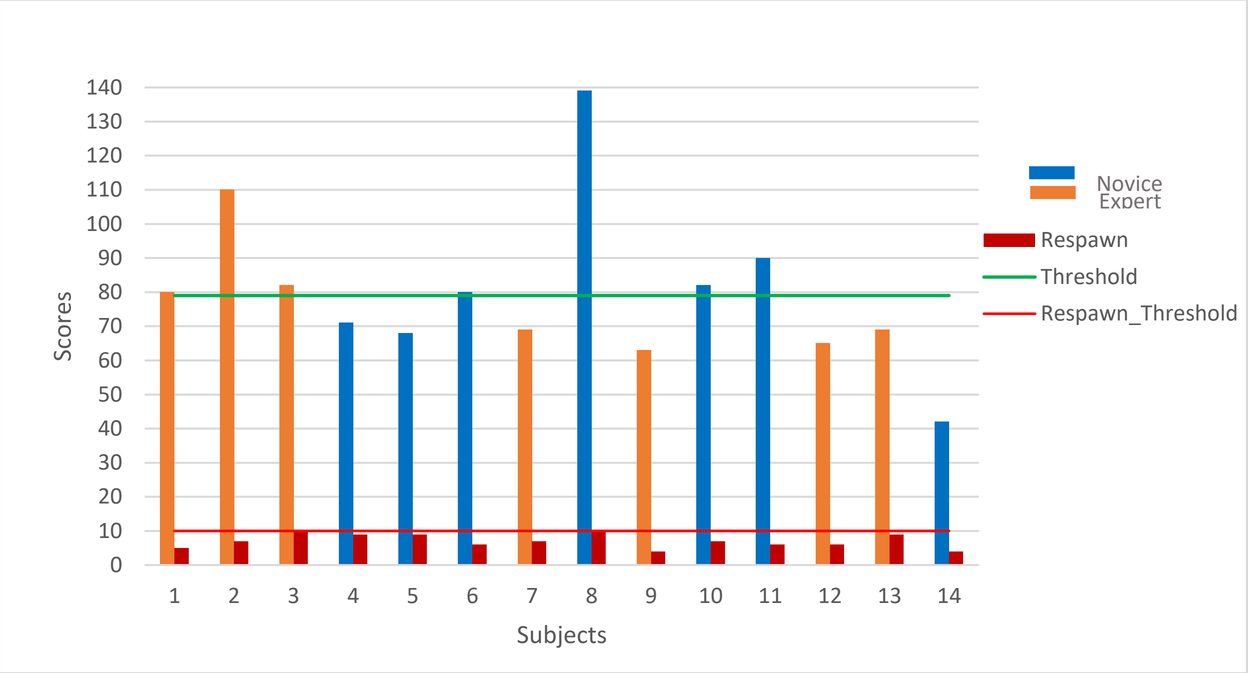


Fig 5.2: Expert levels of players (Call of Duty)

There are three difficulty levels in Sudoku: easy, medium, and hard. As the game's level increases, the difficulty level correspondingly rises. Scores are determined by taking into account the participants' level of play (easy, medium, and hard) and the percentage of puzzles completed within the allotted time. The weighted percentage is calculated using the formula below:

Weightage for each level on completion:

- Easy – 1
- Medium – 2
- Hard – 3

Weighted Percentage=(easy percentage×1+medium percentage×2+hard percentage×3)/1+2+3

The average percentage has been selected as the threshold value based on the weighted percentage. Similar to Call of Duty, participants are divided into expert and novice categories here as well. Participants who scored more than 19% of the weighted percentage are assumed to be experts, while those who scored less are considered novices. Fig 5.3 represents the expertise level of subjects in Sudoku gameplay. This methodological approach of classifying experts and novices is integrated into the MATLAB classifiers.

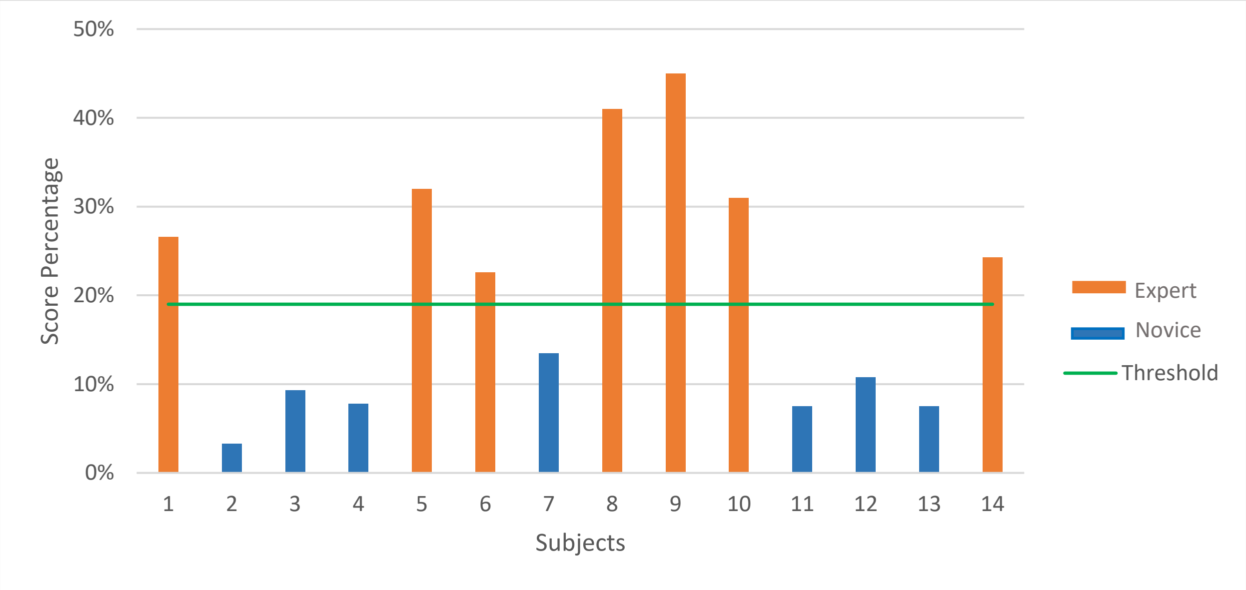


Fig 5.3: Expert levels of players (Sudoku)

The classification into expert and novice groups was then used as input for MATLAB-based machine learning classifiers, which are commonly employed for supervised classification tasks58. These classifiers can include algorithms such as k-nearest neighbors, support vector machines, and Naive Bayes, all of which have been successfully used in previous studies to distinguish between expert and novice game players based on performance and physiological data as shown in Table 5.1.

Table 5.1: Expertise Classification Criteria

Game	Metric(s) Used	Expert Threshold	Novice Threshold
Call of Duty	Enemy kills, respawn status	>79 kills, <10 respawns	79 kills, 10 respawns
Sudoku	Weighted % (by difficulty)	>19% weighted completion	19% weighted completion

5.3 RESULTS OF QUESTIONNAIRE

We tested the mental ability of the subjects through a short mental test before the experiment. As stated earlier, subjects whose MMSE score was less than 25 were excluded from the experiment. Only those with a score higher than 25 were deemed fit to join the experiment. All 14 subject-pairs selected were above this minimum threshold, and none had any sign of cognitive impairment. In addition, the test scores indicate a uniform level of mental alertness among all recruited participants, as illustrated in Fig 5.4 which presents the mini mental statements.

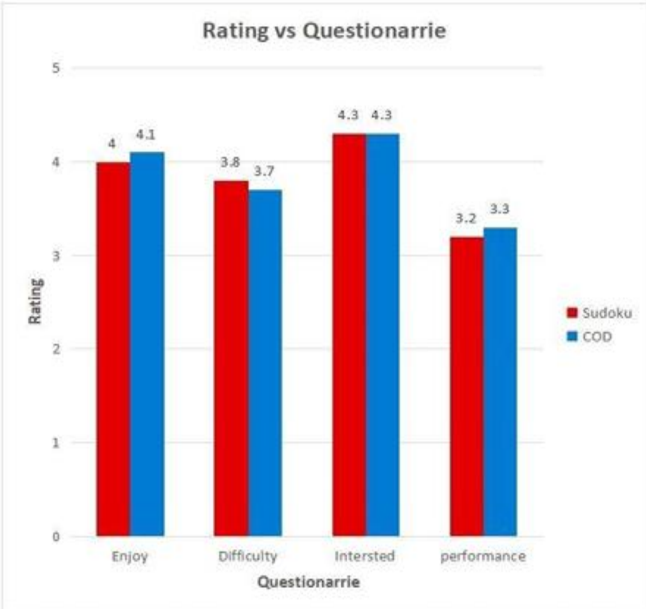


Fig 5.4: Graph of Questionnaire ratings by the participants

5.4 MODEL 1 OUTPUTS

5.4.1 MACHINE LEARNING

In this study, EEG signals were classified based on brain activity recorded during two different mental tasks: playing Sudoku and Call of Duty (COD). The classification was performed channel-wise using MATLAB’s Classification Learner tool. Five machine learning algorithms were tested—Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, Ensemble methods, and Neural Network. The goal was to compare the effectiveness of each algorithm in distinguishing between the tasks using EEG signals from different electrode channels. Confusion matrices were used to evaluate the performance of each model, providing insight into how well each algorithm performed across all 14 channels.

The results highlighted multiple electrodes that showed strong classification performance during both tasks. For the Sudoku task, the most responsive electrodes were P8, O1, O2, and F4, with accuracies of 81.8%, 83.3%, 83.8%, and 85.7% respectively. Similarly, during the Call of Duty task, the electrodes F3, O2, FC6, and F4 recorded high accuracies of 83.4%, 83.6%, 80.9%, and 85.3% respectively, as shown in Table 5.2. These findings indicate that multiple regions of the brain are actively involved during both gaming tasks, and that certain electrode positions, especially in the frontal and occipital regions, play a key role in distinguishing mental states during gameplay. The Neural Network model consistently captured these patterns effectively across channels, supporting its suitability for EEG-based task classification.

Table 5.2: Machine learning output channel wise

Channels	**Sudoku (in percentage)**					**Call Of Duty (in percentage)**				
	Tree	**SVM**	**K-NN**	**Ensem ble**	**Neural**	**Tree**	**SVM**	**K-NN**	**Ensem ble**	**Neural**
AF3	75.3	74	73	78.5	78.3	79.2	76.7	74	82	80.4
F7	72.2	70.8	70.2	75.8	74.3	75.9	74.5	69.7	79.8	78.8
F3	67.4	70.5	65.3	72.7	72.7	80.7	80.7	70.8	83.4	83.2
FC5	69.2	69.1	64.9	74.2	74.9	69.7	70.5	67.1	75.6	75.5
T7	72.6	73.9	71.5	77.5	77.3	72.8	73.1	70.5	77.3	76.6
P7	74.6	74.3	69.9	78.8	78.6	75.5	74.6	73	77.3	77.8
O1	79.4	79.9	77.7	83.3	82.5	79.6	74.5	72.3	77.3	81.9
O2	77.9	82.1	80	83.5	83.8	81.5	78	76.2	77.3	83.6
P8	67.2	79.2	76.8	81.8	82	75.8	76.4	74.9	77.3	79.2
T8	72.9	75.9	73.3	76.8	78.4	68.5	68.7	66.4	77.3	71.7
FC6	75.6	75.1	73.6	79.6	78.4	78.9	75.4	73.2	77.3	80.9

F4	82.3	79.6	77.1	85.2	85.7	82.8	82.6	78.7	84.9	85.3
F8	68.7	67.9	65.7	70.1	71.6	77.3	74.1	69	78.1	77.9
AF4	73	71.2	67.7	75.9	74.6	75.5	70.1	68.5	79	75.7

5.4.2 DEEP LEARNING

The deep learning model, which is implemented using Python in a Jupyter Notebook environment, analyzes EEG data to identify meaningful patterns associated with different gaming tasks. The objective of the model is to accurately classify the tasks by learning from the brainwave signals and distinguishing between them based on the data captured by the 14 EEG electrodes. The classification is performed channel-wise, and the results are carefully evaluated to understand how well the model performs for each electrode and task.

With a strong accuracy of approximately 85%, the model has successfully captured the subtle differences between the two gaming tasks. For the Sudoku task, the most responsive electrodes were O1 (82%), O2 (83%), F4 (85%), P8 (81%), and FC6 (81%), while in the Call of Duty task, key performing electrodes included F3 (84%), O1 (84%), F4 (85%), and AF3 (83%), as presented in Table 5.3. These results suggest that different brain regions contribute significantly to cognitive processing depending on the nature of the game, particularly in the frontal and occipital areas. The deep learning architecture, likely designed to capture both spatial and temporal dynamics of EEG data, proved effective in learning these complex patterns. This reinforces the model's suitability for EEG-based classification tasks and its broader potential in applications like real-time gaming analytics, neurofeedback, and mental state assessment.

Table 5.3: Deep Learning Output Channel wise

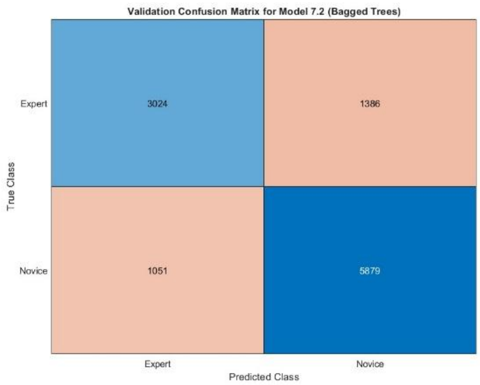
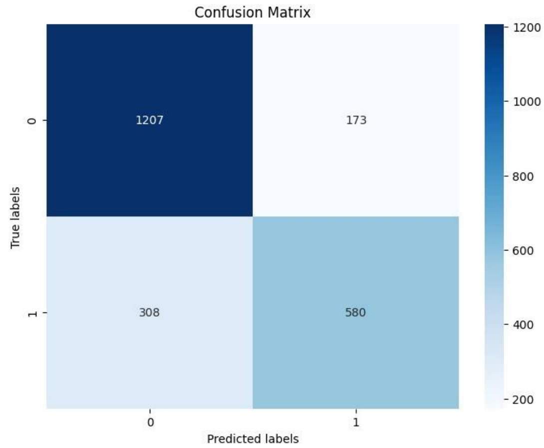
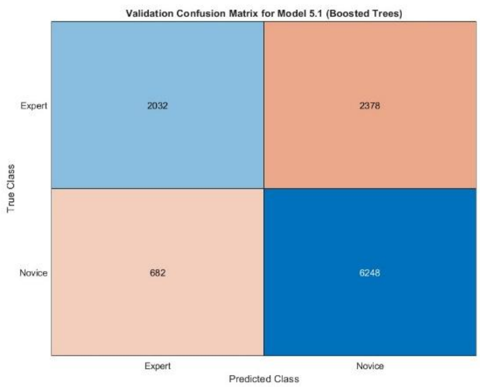
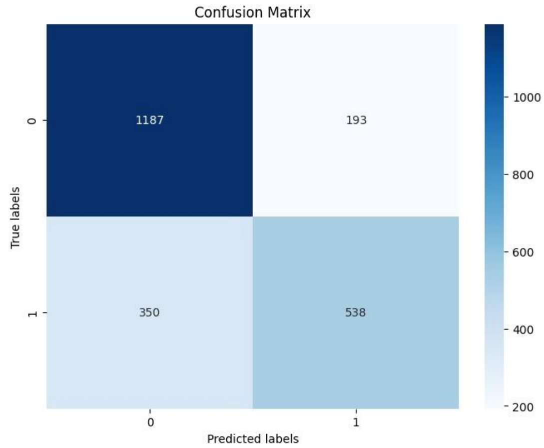
channels	Suduko (in percentage)					Call of Duty in percentage)				
	Test Accuracy	Accuracy	Precison	Recall	f1-score	Test Accuracy	Accuracy	precison	Recall	f1-score
AF3	0.495	0.79	0.785	0.76	0.77	0.595	0.83	0.825	0.805	0.81
F7	0.47	0.76	0.755	0.735	0.735	0.465	0.78	0.78	0.75	0.755
F3	0.495	0.74	0.725	0.71	0.715	0.525	0.84	0.83	0.815	0.82
FC5	0.49	0.75	0.745	0.715	0.72	0.465	0.75	0.74	0.815	0.82
T7	0.55	0.77	0.765	0.735	0.74	0.475	0.78	0.775	0.745	0.755
P7	0.515	0.79	0.79	0.76	0.77	0.56	0.8	0.805	0.775	0.785
O1	0.495	0.82	0.82	0.805	0.81	0.515	0.84	0.84	0.83	0.83
O2	0.54	0.83	0.835	0.815	0.82	0.51	0.75	0.74	0.72	0.73
P8	0.54	0.81	0.8	0.79	0.79	0.415	0.8	0.795	0.78	0.785
T8	0.44	0.78	0.775	0.75	0.76	0.445	0.74	0.725	0.7	0.71
FC6	0.485	0.81	0.815	0.79	0.8	0.515	0.82	0.815	0.815	0.815
F4	0.495	0.85	0.845	0.84	0.84	0.5	0.85	0.845	0.84	0.845
F8	0.51	0.7	0.69	0.665	0.665	0.56	0.78	0.78	0.75	0.76
AF4	0.47	0.77	0.765	0.755	0.76	0.515	0.8	0.79	0.78	0.785

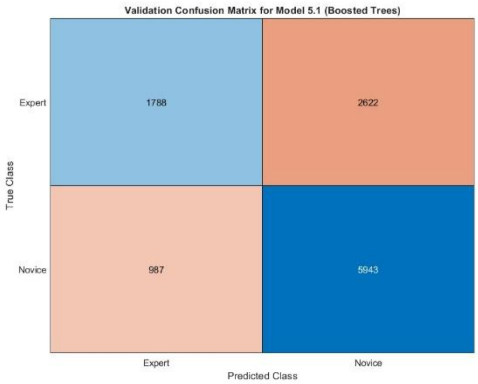
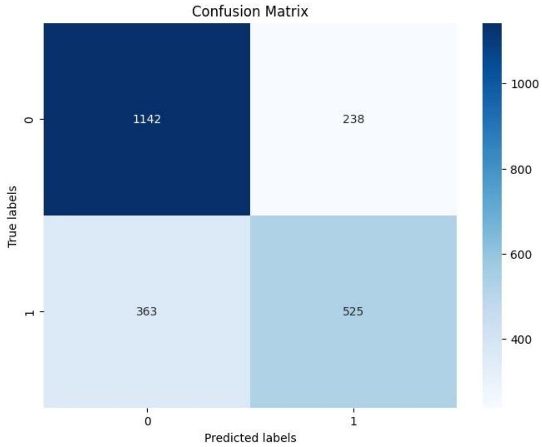
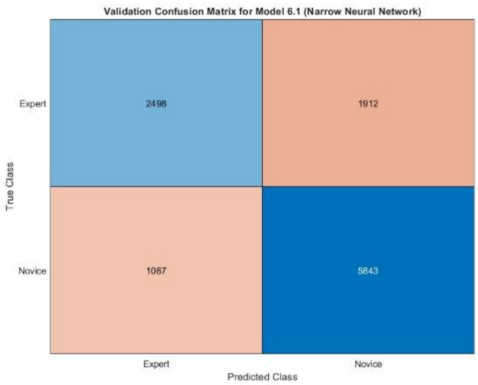
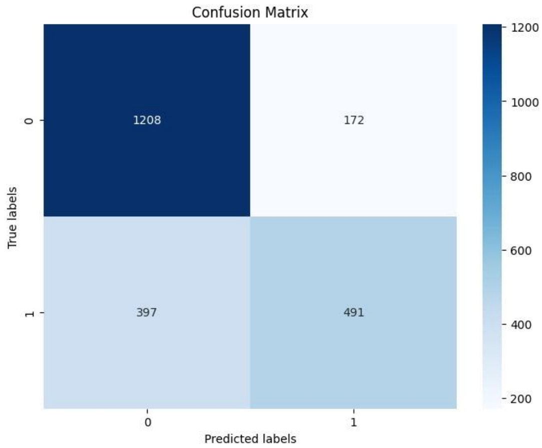
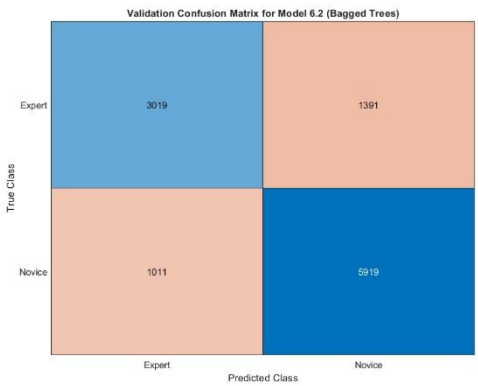
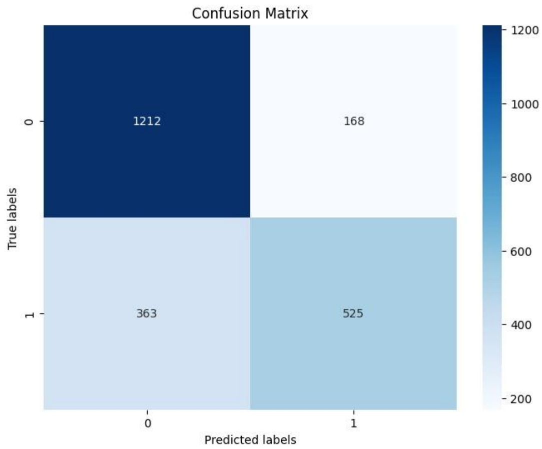
5.4.3 CONFUSION MATRIX

Sections 5.4.1 and 5.4.2 present in-depth comparisons between machine learning and deep learning techniques applied to EEG recordings obtained while performing two games: Sudoku and Call of Duty. Through the machine learning method Section 5.4.1, five algorithms such as SVM, KNN, Decision Tree, Ensemble methods, and Neural Network were implemented to classify channel-wise EEG signals through MATLAB's Classification Learner tool. Of all the channels, the F4 channel was always the one that gave the best performance, with accuracy at 85.7% for Sudoku and 85.3% for Call of Duty, as shown in Table 5.4 and Table 5.5, respectively. The confusion matrices of these tasks indicated strong diagonal dominance, which represented high accuracy and low misclassification for the F4 channel.

Conversely, Section 5.4.2 explains the deep learning method, wherein a Python model developed in Jupyter Notebook was employed to categorize the same EEG data. This model produced an average accuracy of approximately 85%, and the most informative channel for both tasks was once again F4. The confusion matrices for deep learning attested that the model was able to learn the underlying patterns of brain activity with a good prediction ability. In comparing both approaches, it was noted that while machine learning showed high accuracy in certain channels, deep learning had greater consistency over multiple channels and was able to capture spatial as well as temporal features more accurately. This comparative outcome is also evident from the channel-wise accuracy image, where the F4 channel is emphasized in both methods. Therefore, Tables 5.4 and 5.5 and the corresponding confusion matrices clearly show that although both methods are efficient, deep learning provides better generalization and flexibility for EEG-based gaming task classification.[17]

Table 5.4: Sudoku Output for Machine Learning and Deep Learning Channel wise

Channel	Machine Learning	Deep Learning
AF3		
F7		

F3	Validation Confusion Matrix for Model 5.1 (Boosted Trees) True Class Expert Novice 1788 2622 987 5943 Expert Novice Predicted Class	Confusion Matrix True labels 0 1 1142 238 363 525 0 1 Predicted labels 1000 800 600 400
FC5	Validation Confusion Matrix for Model 6.1 (Narrow Neural Network) True Class Expert Novice 2498 1912 1087 5843 Expert Novice Predicted Class	Confusion Matrix True labels 0 1 1208 172 397 491 0 1 Predicted labels 1200 1000 800 600 400 200
T7	Validation Confusion Matrix for Model 6.2 (Bagged Trees) True Class Expert Novice 3019 1391 1011 5919 Expert Novice Predicted Class	Confusion Matrix True labels 0 1 1212 168 363 525 0 1 Predicted labels 1200 1000 800 600 400 200

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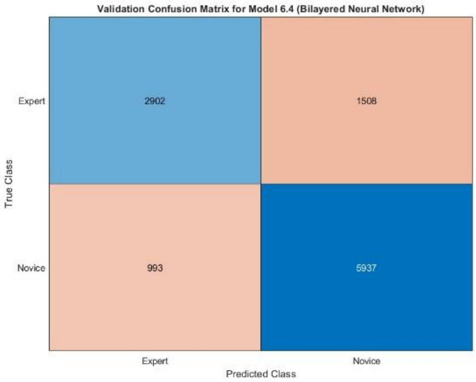
<td>
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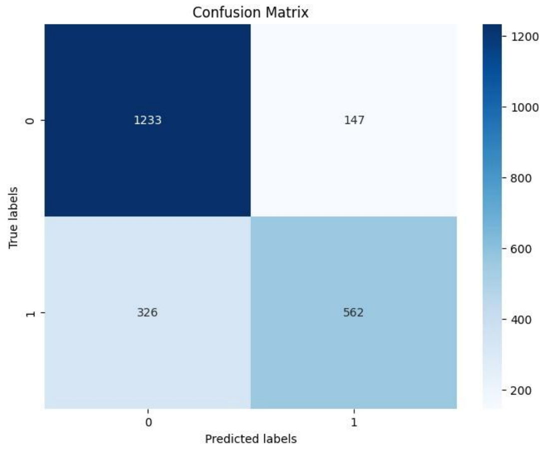
<td>
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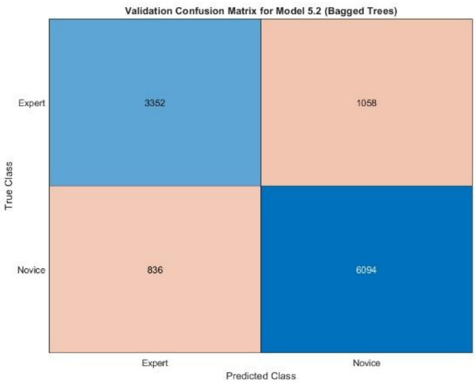
<td>
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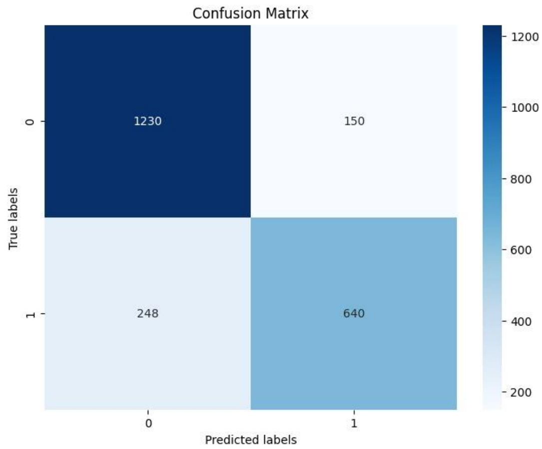
<td>
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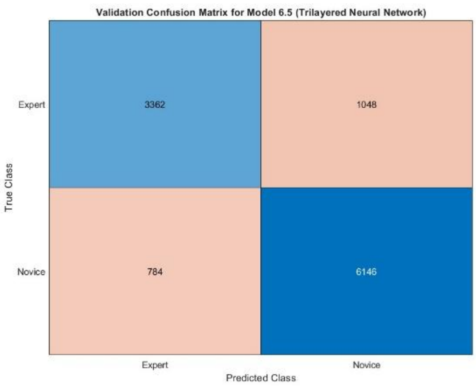
<td>
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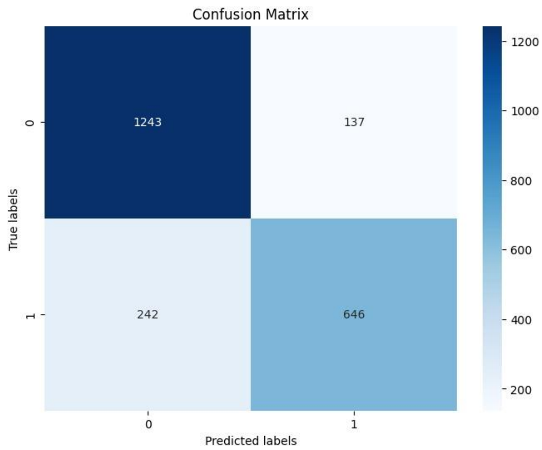
<td>
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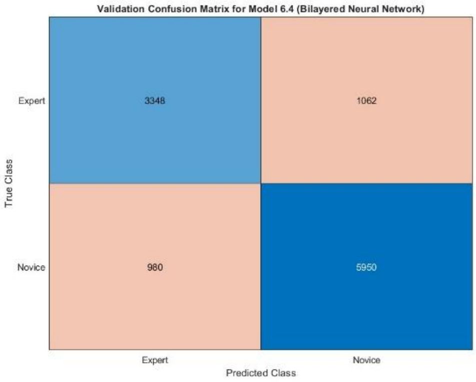
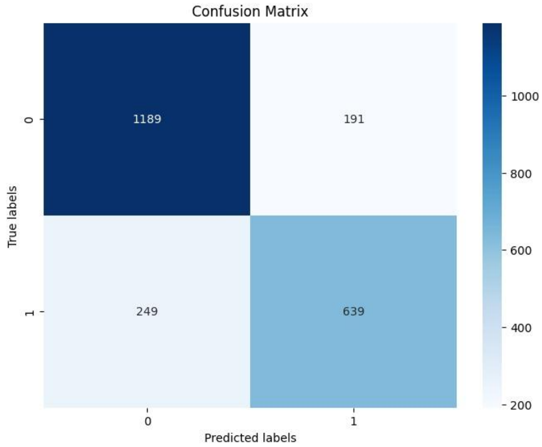
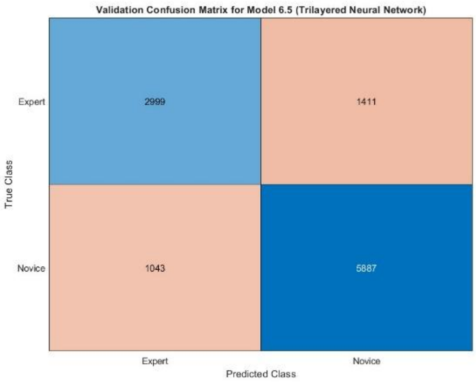
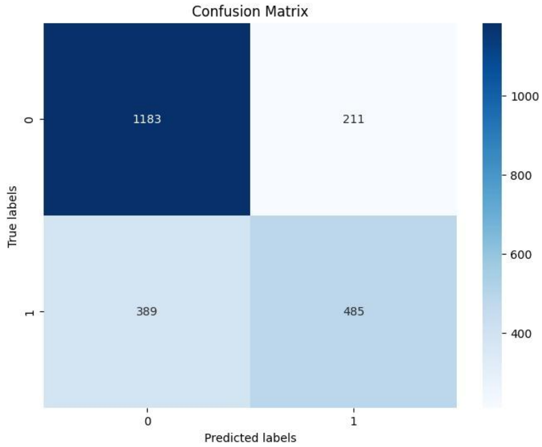
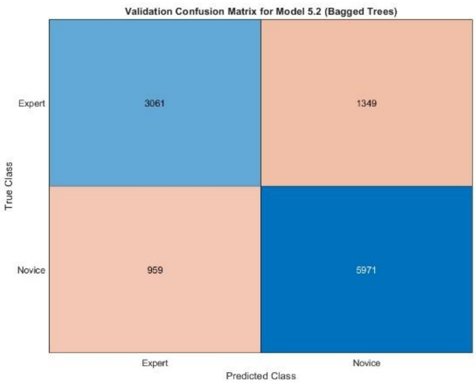
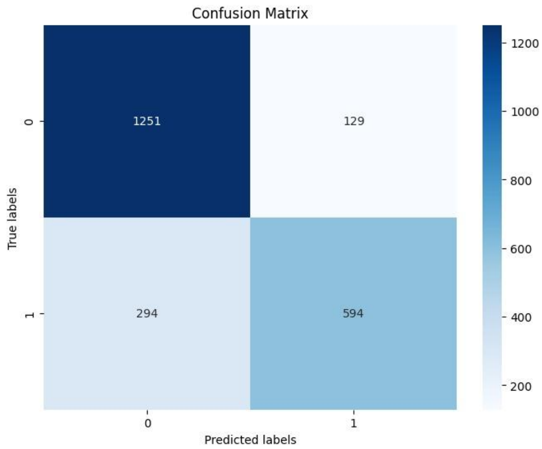
P8	Validation Confusion Matrix for Model 6.4 (Bilayered Neural Network) True Class Expert Novice 3348 1062 980 5950 Expert Novice Predicted Class	Confusion Matrix True labels 0 1 1189 191 249 639 0 1 Predicted labels 1000 800 600 400 200
T8	Validation Confusion Matrix for Model 6.5 (Trilayered Neural Network) True Class Expert Novice 2999 1411 1043 5887 Expert Novice Predicted Class	Confusion Matrix True labels 0 1 1183 211 389 485 0 1 Predicted labels 1000 800 600 400
FC6	Validation Confusion Matrix for Model 5.2 (Bagged Trees) True Class Expert Novice 3061 1349 959 5971 Expert Novice Predicted Class	Confusion Matrix True labels 0 1 1251 129 294 594 0 1 Predicted labels 1200 1000 800 600 400 200

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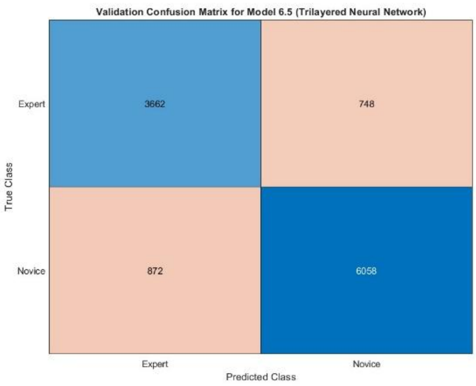
<td>
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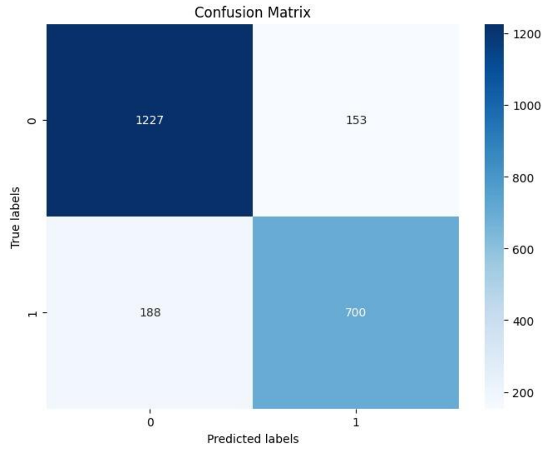
<td>
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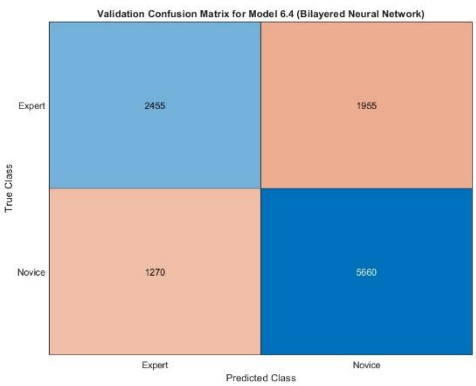
<td>
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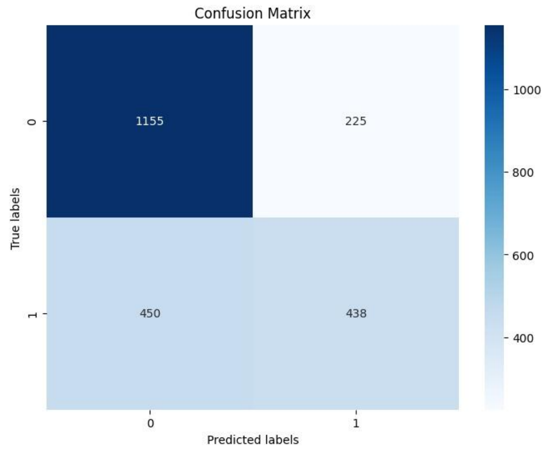
<td>
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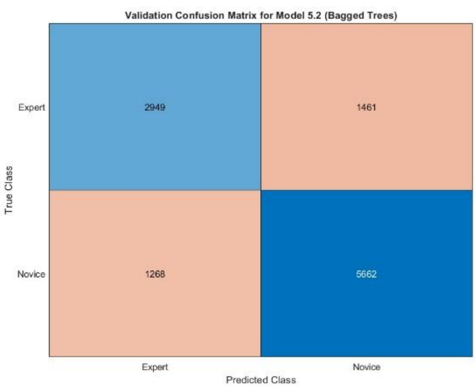
<td>
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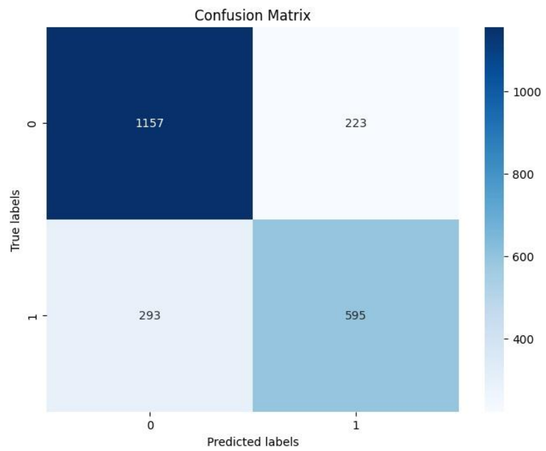
<td>
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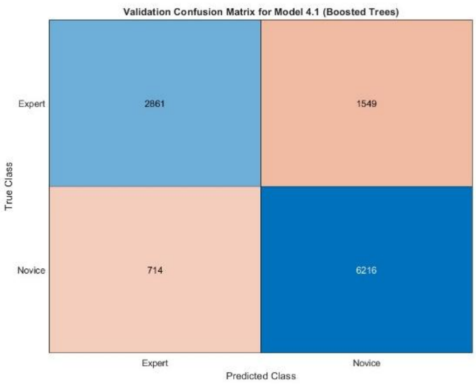
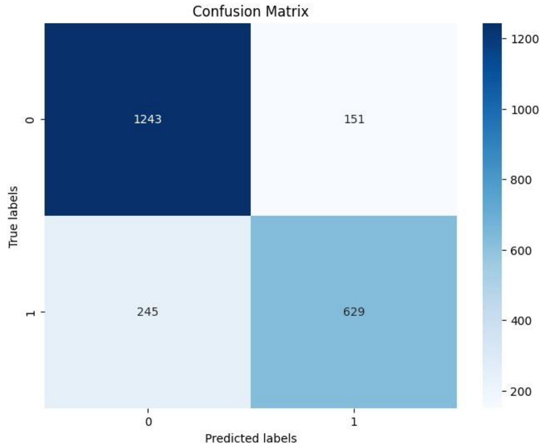
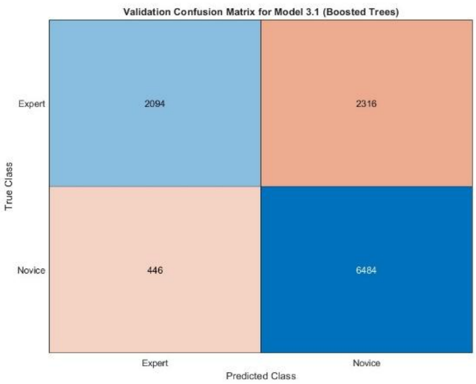
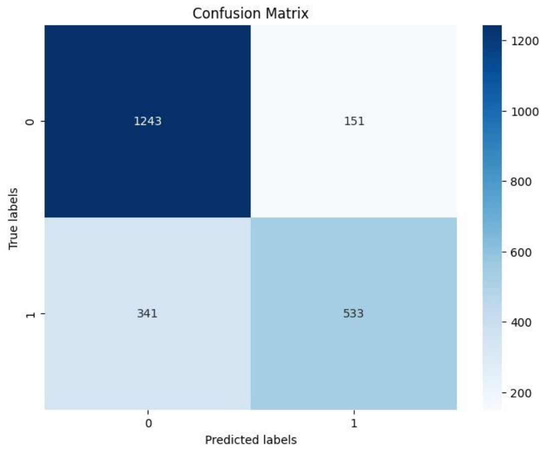
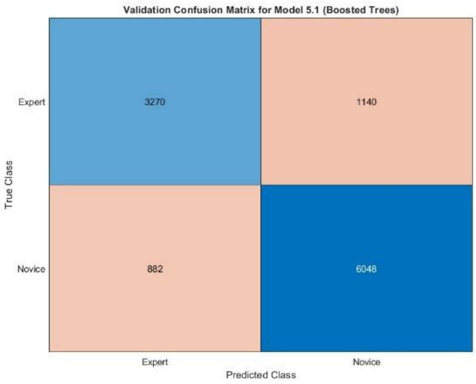
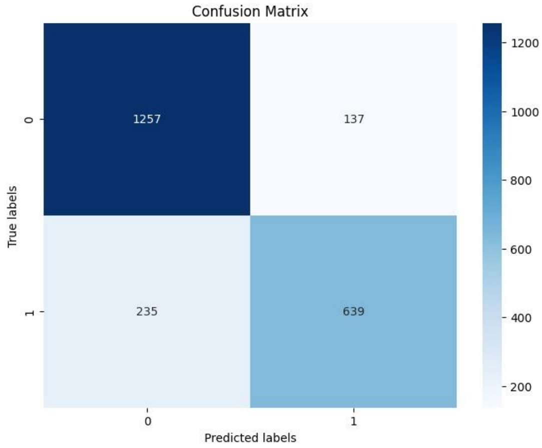
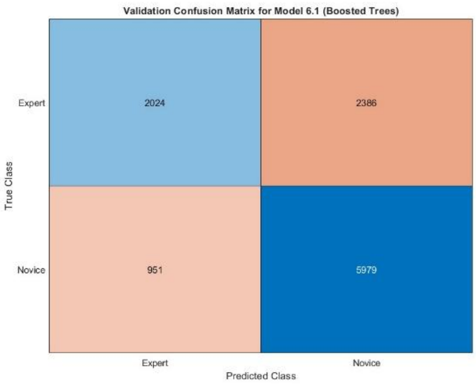
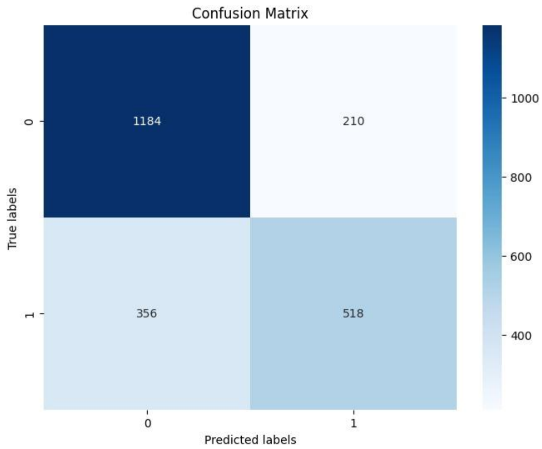
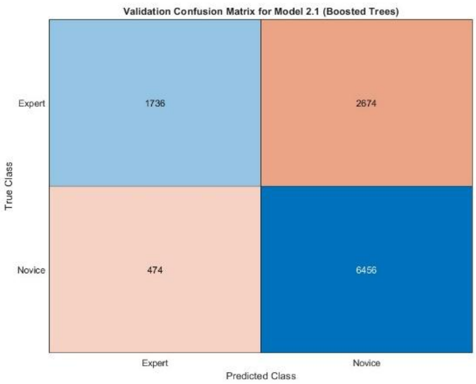
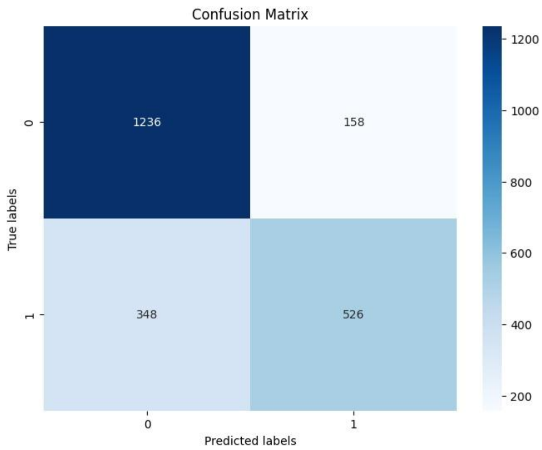
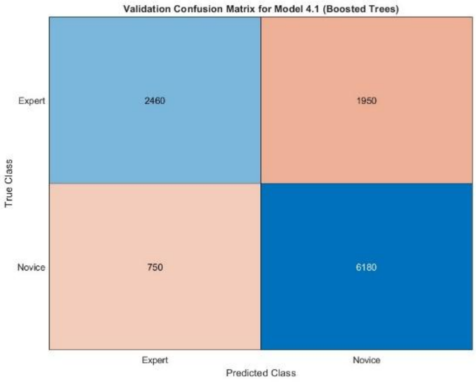
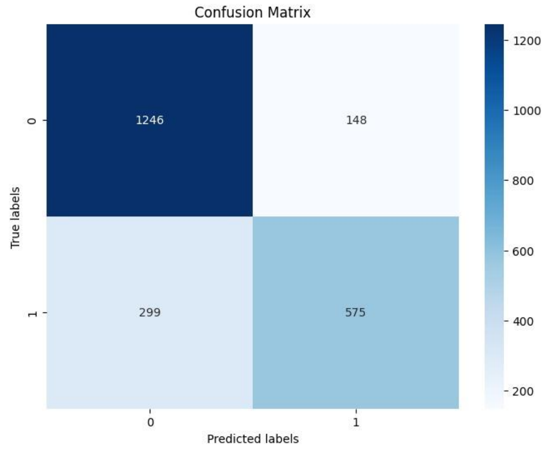
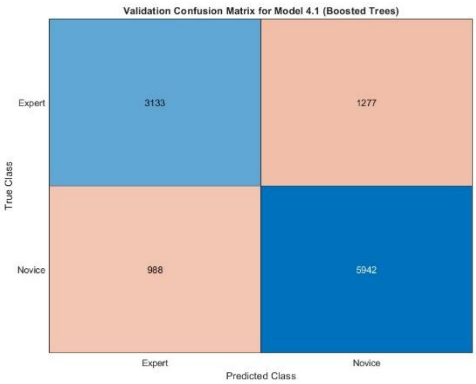
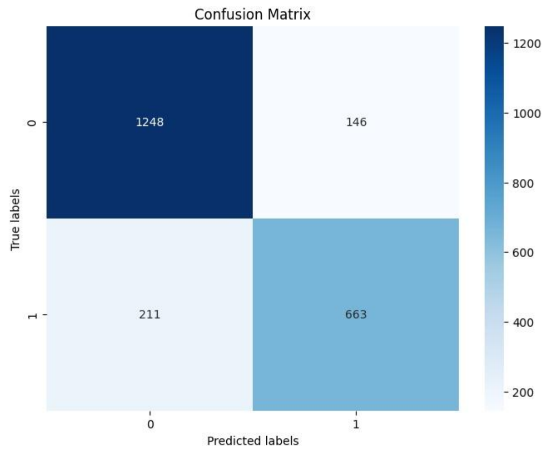
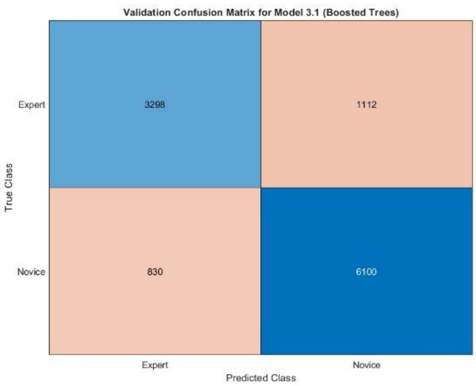
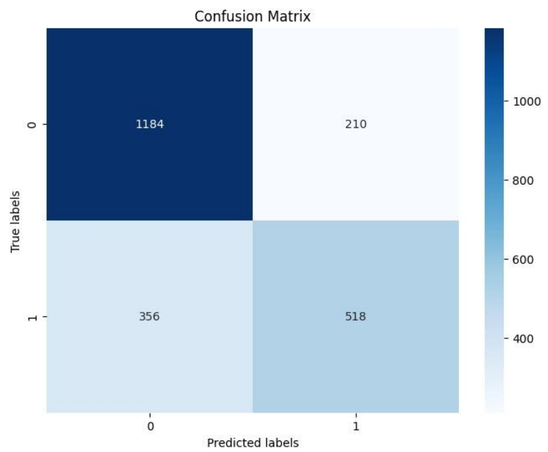
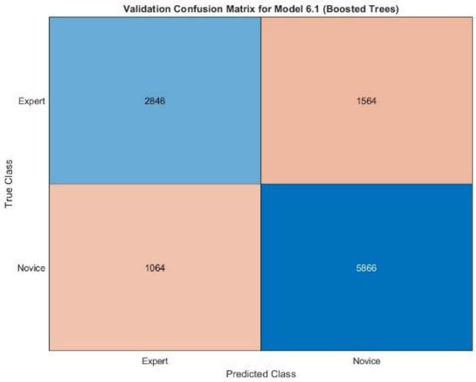
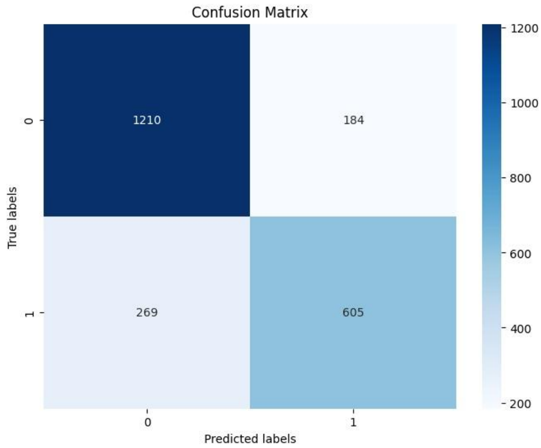
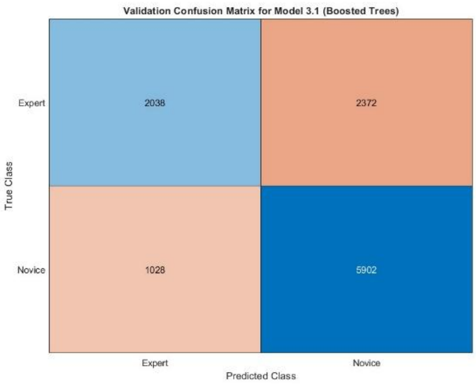
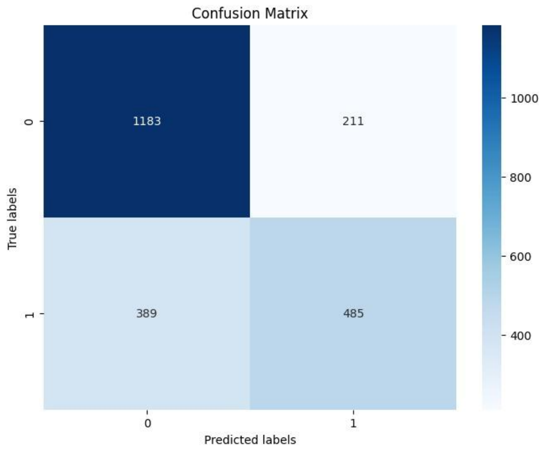
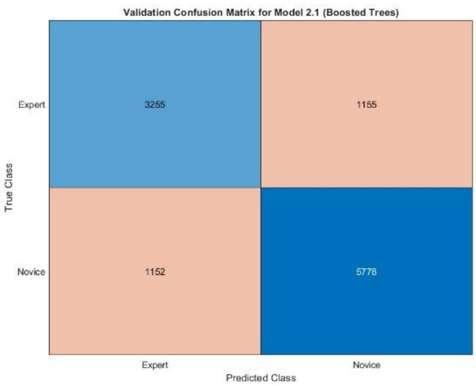
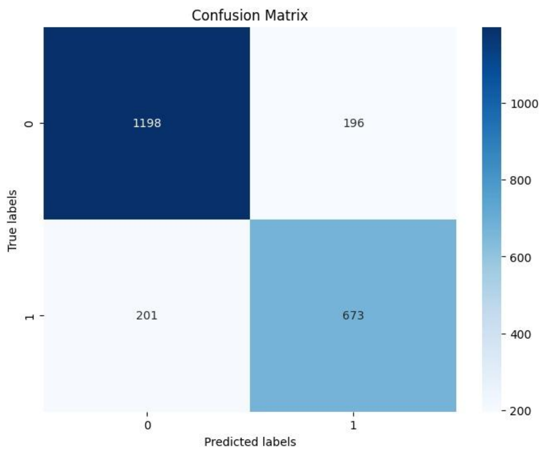
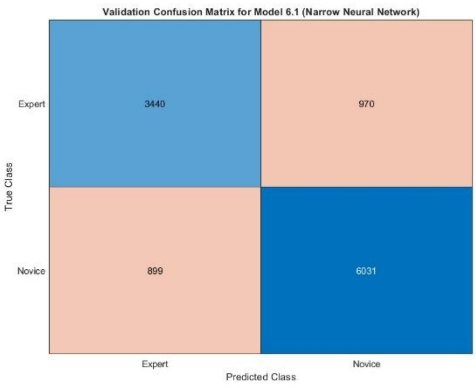
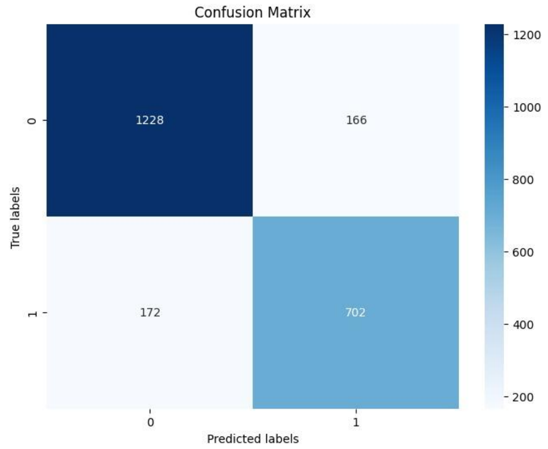
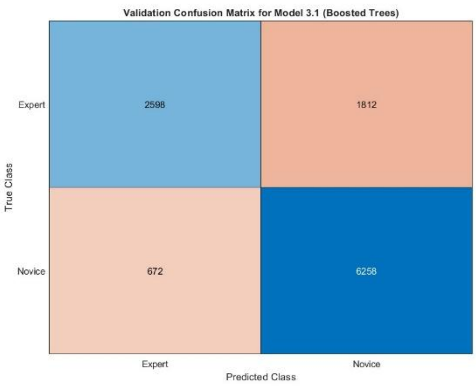
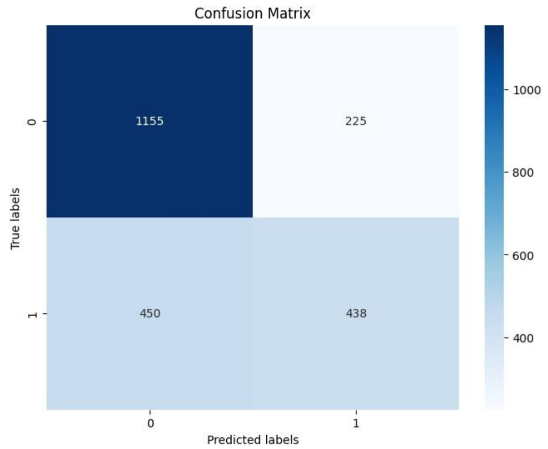
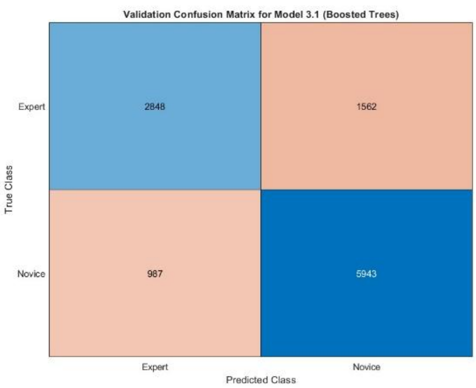
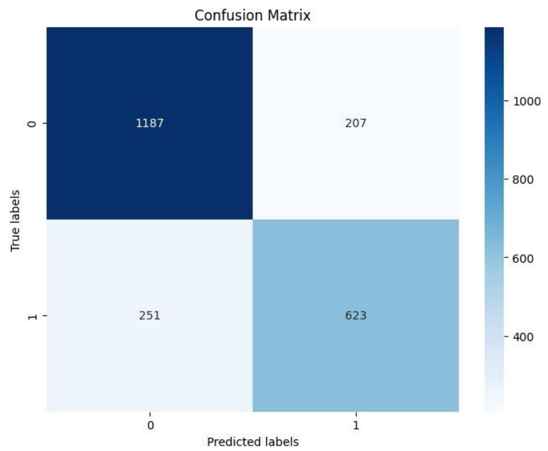
Table 5.5: COD Output for Machine Learning and Deep Learning Channel wise

Channel	Machine Learning	Deep Learning
AF3		
F7		

F3	Validation Confusion Matrix for Model 5.1 (Boosted Trees) Expert Novice 3270 1140 882 6048 True Class Predicted Class	Confusion Matrix 1257 137 235 639 True labels Predicted labels
FC5	Validation Confusion Matrix for Model 6.1 (Boosted Trees) Expert Novice 2024 2386 951 5979 True Class Predicted Class	Confusion Matrix 1184 210 356 518 True labels Predicted labels
T7	Validation Confusion Matrix for Model 2.1 (Boosted Trees) Expert Novice 1736 2674 474 6456 True Class Predicted Class	Confusion Matrix 1236 158 348 526 True labels Predicted labels

P7	Validation Confusion Matrix for Model 4.1 (Boosted Trees) True Class Expert Novice 2460 1950 750 6180 Predicted Class	Confusion Matrix True labels Predicted labels 1246 148 299 575
O1	Validation Confusion Matrix for Model 4.1 (Boosted Trees) True Class Expert Novice 3133 1277 988 5942 Predicted Class	Confusion Matrix True labels Predicted labels 1248 146 211 663
O2	Validation Confusion Matrix for Model 3.1 (Boosted Trees) True Class Expert Novice 3298 1112 830 6100 Predicted Class	Confusion Matrix True labels Predicted labels 1184 210 356 518

P8	Validation Confusion Matrix for Model 6.1 (Boosted Trees) True Class Expert Novice 2846 1564 1064 5866 Expert Novice Predicted Class	Confusion Matrix True labels 0 1 1210 184 269 605 0 1 Predicted labels 1200 1000 800 600 400 200
T8	Validation Confusion Matrix for Model 3.1 (Boosted Trees) True Class Expert Novice 2038 2372 1028 5902 Expert Novice Predicted Class	Confusion Matrix True labels 0 1 1183 211 389 485 0 1 Predicted labels 1000 800 600 400
FC6	Validation Confusion Matrix for Model 2.1 (Boosted Trees) True Class Expert Novice 3255 1155 1152 5778 Expert Novice Predicted Class	Confusion Matrix True labels 0 1 1198 196 201 673 0 1 Predicted labels 1000 800 600 400 200

F4	Validation Confusion Matrix for Model 6.1 (Narrow Neural Network) True Class Expert Novice 3440 970 899 6031 Expert Novice Predicted Class	Confusion Matrix True labels 0 1 1228 166 172 702 0 1 Predicted labels 1200 1000 800 600 400 200
F8	Validation Confusion Matrix for Model 3.1 (Boosted Trees) True Class Expert Novice 2598 1812 672 6258 Expert Novice Predicted Class	Confusion Matrix True labels 0 1 1155 225 450 438 0 1 Predicted labels 1000 800 600 400
AF4	Validation Confusion Matrix for Model 3.1 (Boosted Trees) True Class Expert Novice 2848 1562 987 5943 Expert Novice Predicted Class	Confusion Matrix True labels 0 1 1187 207 251 623 0 1 Predicted labels 1000 800 600 400

5.5 MODEL 2 OUTPUTS

5.5.1 SCALOGRAM

The input to this process, as described in Algorithm 5.1, is raw EEG data stored in CSV format, sampled at 256 Hz from 14 different electrode channels. This data represents brain activity recorded over a 5-minute gaming session. The goal is to transform this raw time-series signal into a format suitable for deep learning specifically, into 224×224 pixel scalogram images. The EEG signal for each channel is split into 20-second intervals to ensure localized temporal features are preserved.

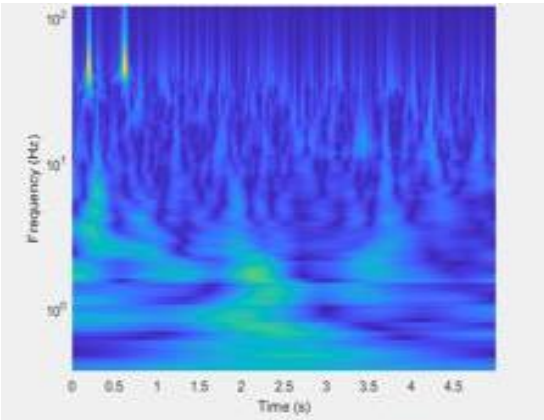


Fig 5.5: Scalogram image

Fig 5.5 shows the scalogram representation of EEG data obtained from the raw EEG signals. A scalogram is a time-frequency plot generated using Continuous Wavelet Transform (CWT), which helps in analyzing the signal's frequency components over time. The x-axis represents time in seconds, and the y-axis represents frequency in Hz on a logarithmic scale. The color intensity indicates the energy level at a particular time and frequency. This visualization is useful for capturing non-stationary features in EEG signals. These scalogram images are further used as input for deep learning models to classify cognitive states such as expert and novice.

Each segment undergoes Continuous Wavelet Transform (CWT), which maps the signal into a time-frequency representation known as a scalogram. These scalograms visually capture important frequency-based changes in brain activity. Each plot is then resized to 224×224 pixels and saved as a JPEG image, forming a dataset of images ready for input into convolutional neural networks. This method provides a powerful way to convert brainwave data into a form that deep learning models can easily learn from, making it suitable for tasks such as gaming activity classification or mental state detection.[13]

Algorithm 5.1: Scalogram image generated code

Input: EEG data (CSV), Sampling rate = 256 Hz, 14 channels

Output: 224×224 scalogram images for each 20s segment per channel

1. **Initialize**: Set file paths, sampling rate, and wavelet parameters [40, 60].
2. **Load EEG Data** from CSV for a total of 5 minutes (21×60×fs samples).
3. **Segment Data**: Divide into 20s intervals (c segments).
4. **For each Channel (1–14)**:
   a. Extract channel data.
   b. For each 20s segment:
      i. Apply Continuous Wavelet Transform (CWT).
      ii. Plot the scalogram with log-frequency.
      iii. Resize to 224×224 and save as JPEG.
5. **Repeat** for all channels.

5.5.2 DATA SIGNAL VS SCALOGRAM

In the second phase of the study, we shifted from channel-wise classification to an overall approach by analyzing complete EEG data from all 14 channels combined. We first processed the raw EEG signals directly using a deep learning model, without isolating individual channels. In parallel, we generated scalogram images from the same EEG data to represent the time-frequency characteristics visually and used these images as input to another deep learning model. This dual approach enabled us to evaluate and compare the effectiveness of both data formats in classifying the two gaming tasks—Sudoku and Call of Duty.

The results of this overall analysis, summarized in Table 5.6 and 5.7, provided a broader view of model performance. For raw EEG signal input, the deep learning model achieved an accuracy of 0.74 for Call of Duty and 0.73 for Sudoku. When using scalogram images, the accuracy was 0.72 for Call of Duty and 0.73 for Sudoku. These findings suggest that both raw signal and scalogram-based approaches are effective, with the raw EEG data offering slightly better performance for the Call of Duty task. This indicates that deep learning can capture cognitive variations between tasks even without separating data channel-wise, making it suitable for real-time applications involving complex mental activities.

Table 5.6: Over all Output for Deep Learning

Channels	Data Signal (in percentage)					Scalogram (in percentage)				
	Test Accuracy	Model Accuracy	Precison	Recall	f1-score	Test Accuracy	Model Accuracy	Precison	Recall	f1-score
COD	0.5099	0.74	0.73	0.71	0.715	0.7008	0.72	0.7	0.7	0.7
Sudoku	0.565	0.73	0.74	0.735	0.73	0.565	0.73	0.73	0.73	0.73

Table 5.7: Overall Output for Data signal and Deep Learning

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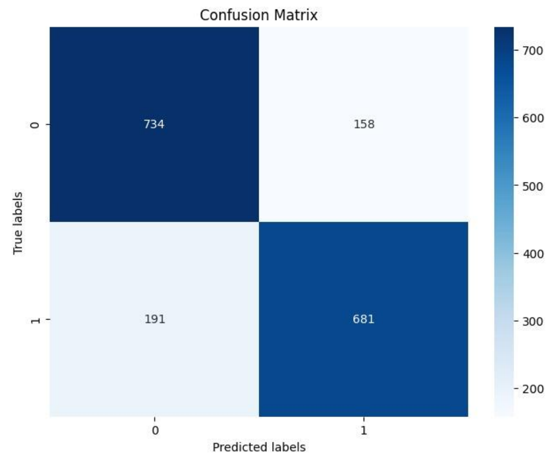

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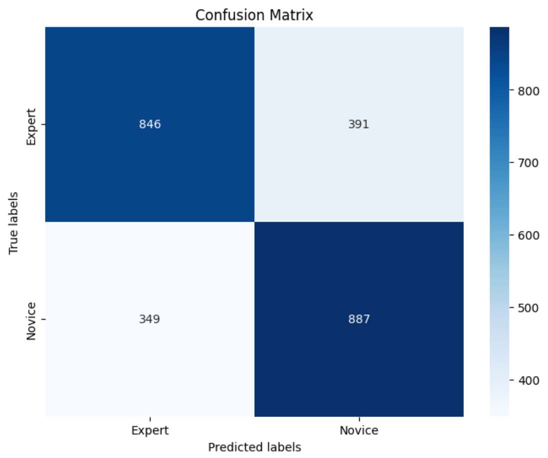

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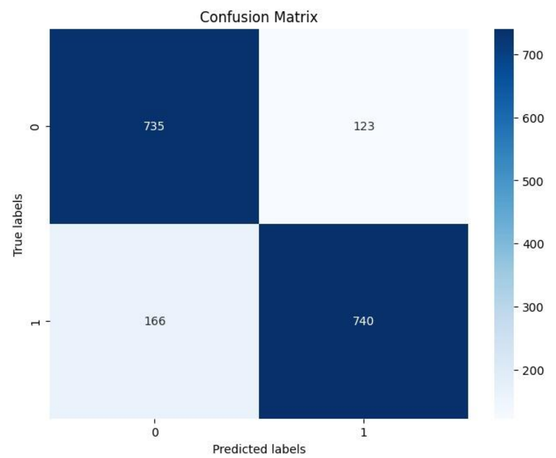
<tr><td>COD</td><td>


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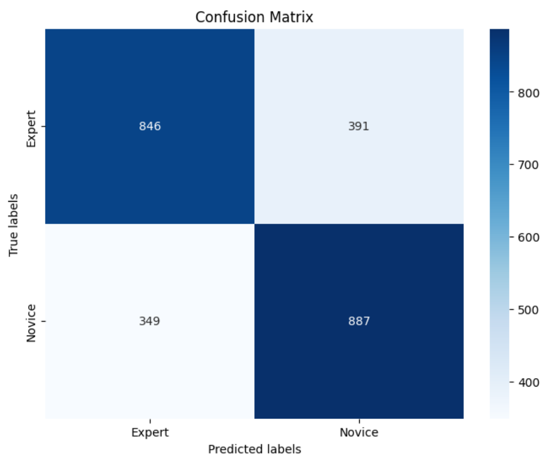

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</table>

CHAPTER 6
DISCUSSION

This study focused on classifying EEG signals collected during two different mental tasks—Sudoku and Call of Duty (COD). In Model 1, the EEG data were analyzed channel-wise using both machine learning and deep learning techniques independently. For the machine learning approach, MATLAB's Classification Learner tool was used with five algorithms: SVM, KNN, Decision Tree, Ensemble methods, and Neural Network. Each of the 14 EEG channels was evaluated individually to determine which electrode gave the highest classification accuracy for each task. Similarly, a deep learning model was developed and applied separately to each channel to observe how well it could learn from the temporal patterns in the signal.

From this analysis, it was observed that four electrodes in particular—F4, O1, O2, and P8 for Sudoku, and F4, F3, O1, and AF3 for COD—showed dominant performance across both ML and DL models. These results confirm that task-related brain activity is especially strong in the frontal and occipital regions, which are crucial for attention and decision-making processes. Moreover, although ML and DL were handled as separate models, both approaches consistently highlighted the same key electrodes, reinforcing the reliability of these regions for EEG-based task classification. The use of confusion matrices in both approaches allowed for a clear and comparative evaluation of model performance across different channels.

In the second phase of our study, we shifted from channel-wise classification to a more comprehensive approach by analyzing the entire EEG data from all 14 channels. We compared two methods: one using raw EEG signals directly processed by a deep learning model, and another using scalogram images of the EEG data to capture time-frequency characteristics. The results showed that both methods were effective, with the raw EEG signals achieving slightly better accuracy for the Call of Duty task (74%) compared to scalogram images (72%), while both methods performed similarly for the Sudoku task (73%). This indicates that deep learning can successfully classify gaming tasks without the need to separate individual EEG channels, making it a promising approach for real-time applications that require complex cognitive task classification.

CHAPTER 7
CONCLUSION

7.1 CONCLUSION OF THE RESEARCH

In Model 1, EEG data collected during the tasks of Sudoku and Call of Duty (COD) were analyzed separately using both Machine Learning (ML) and Deep Learning (DL) techniques on a channel-wise basis. In the Sudoku task, ML classification showed high performance in the F4 (85.7%), O2 (83.8%), O1 (83.3%), and P8 (81.8%) channels. Similarly, DL classification for Sudoku highlighted the same channels with slightly varying accuracies—F4 (85%), O2 (83%), O1 (82%), P8 (81%), and FC6 (81%). For the COD task, ML showed dominant performance in F4 (85.3%), F3 (83.4%), O2 (83.6%), and FC6 (80.9%), while DL also pointed to F4 (85%), F3 (84%), O1 (84%), and AF3 (83%) as the most informative electrodes.

This channel-wise analysis from both ML and DL shows significant activation in the frontal (F3, F4, FC6, AF3), occipital (O1, O2), and parietal (P8) lobes during gaming tasks. In the Sudoku task, higher activity in O1, O2, and P8 indicates greater involvement of the occipital and parietal lobes, which are responsible for visual processing, spatial reasoning, and logical reasoning needed for solving puzzles. The frontal lobe channels F4 and FC6 are also engaged, supporting logical thinking, decision-making, and planning. In contrast, the Call of Duty (COD) task showed dominant activation in frontal channels (F3, F4, FC6, AF3), reflecting the attention, decision-making, reaction control, and strategic planning necessary for fast-paced gameplay. The occipital lobe channels O1 and O2 were also active, responsible for visual processing, crucial for tracking targets, movement, and in-game environments. These results highlight the distinct cognitive demands of each game, with frontal, occipital, and parietal lobes engaged depending on the task, and ML and DL both consistently identifying similar key electrode regions.

In Model 2, the study demonstrated that both raw EEG signals and scalogram images are effective for classifying gaming tasks such as Sudoku and Call of Duty. The deep learning model achieved an accuracy of 0.74 for Call of Duty and 0.73 for Sudoku when using raw EEG signals. For the scalogram images, the accuracy was 0.72 for Call of Duty and 0.73 for Sudoku. These results indicate that both data formats are viable, with the raw EEG data slightly outperforming the scalogram-based approach for the Call of Duty task. Overall, this analysis suggests that deep learning models can capture cognitive differences between tasks without isolating individual EEG channels, making them suitable for real-time applications involving complex mental activities.

7.2 FUTURE SCOPE

Building on the findings of this study, future research can focus on developing more advanced real-time systems that leverage deep learning models for cognitive task classification. One promising application is in adaptive gaming systems that adjust difficulty levels based on a player's cognitive state, providing a more personalized and engaging experience. Moreover, the ability to classify mental states from raw EEG data can be applied to real-time health monitoring systems, especially for mental health conditions like ADHD or stress management. As EEG technology improves, this approach could also be used to enhance brain-computer interfaces (BCIs), allowing users to interact with devices using cognitive signals alone. Furthermore, integrating this EEG-based classification into educational platforms could tailor learning experiences based on students' cognitive engagement, maximizing their potential for learning and problem-solving.

APPENDIX – A

Batch-15

by M Sudha

General metrics

62,721	9,285	976	37 min 8 sec	1 hr 11 min
characters	words	sentences	reading time	speaking time

Score

81

This text scores better than 81% of all texts checked by Grammarly

Writing Issues

367	89	278
Issues left	Critical	Advanced

Plagiarism

This text seems 100% original. Grammarly found no matching text on the Internet or in ProQuest's databases.

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