

AI BASED ANALYSIS OF ELIMENTORY COGNITIVE BLOOMS TOXONOMY TASKS USING BIOPAC EEG SIGNALS

Submitted in partial fulfilment of the requirements for the award of
Bachelor of Technology in Biomedical Engineering

By

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**DEPARTMENT OF BIOMEDICAL ENGINEERING
SCHOOL OF BIO AND CHEMICAL ENGINEERING**

SATHYABAMA
INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)

Accredited with Grade "A++" by NAAC
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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Rishon V (40240026)** who have done the project work and carried out the project entitled "**AI based Analysis of elementary cognitive Blooms Taxonomy tasks using Biopac EEG signals**" under our supervision from July 2023 to April 2024.


Internal Guide

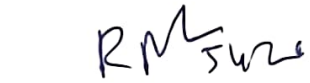
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Internal Examiner


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DECLARATION

I **Rishon V** hereby declare that the Project Report entitled “**AI based Analysis of elementary cognitive Blooms Taxonomy tasks using Biopac EEG signals**” done by us under the guidance of **Dr. T. SUDHAKAR** is submitted in partial fulfillment of the requirements for the award of Bachelor of Technology degree in Biomedical Engineering.

DATE: 05.04.2024

SIGNATURE OF THE CANDIDATE

PLACE: CHENNAI

V. RISHON (40240026)

A handwritten signature in black ink, appearing to read 'V. Rishon', with a horizontal line underneath the name.

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ABSTRACT:

This project aims at analyzing EEG during problem solution. The problems will be given according to bloom taxonomy levels. The EEG signals are analyzed during the time when the subjects solve problems with varying the complexity of mathematical and scientific problems which will be given in all the six levels of Blooms taxonomy. The alpha and theta waves of the frontal, parietal and occipital lobes will be analyzed.

Statistical, spectral, and time frequency analysis of EEG signals during problem solving will be analyzed to study about the Brain behavior for reasoning and problem-solving capabilities.

Cognitive test primarily depends on how an individual perceives, assimilates and responds to an external stimulus. We are creating Electroencephalogram (EEG) models for the cognitive skills defined in the Bloom's taxonomy task using Biopac EEG signals. This could be able to provide a individual assistance according to one's learning style and abilities. This project aims at analyzing EEG during problem solution. The problems will be given according to bloom taxonomy levels three basic tasks namely lower level, moderate level, advance level. These tasks help to understand and analyze sub categories of Bloom's taxonomy. Different brain regions are activated while performing the above tasks. However, The EEG signals are analyzed during the time when the subjects solve problems. The cleaned EEG signals are analyzed using scalp-mounted electrode.

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LIST OF ABBREVIATION:

ABBREVIATION	EXPANSION
ADAS	Advanced driver assistance systems
ADHD	Attention Deficit Hyperactivity Disorder
API	Application programming interface
ASMR	Autonomous sensory meridian response
AUC	Area under the ROC curve
BCI	Brain-computer interface
BSL	BIOPAC Student Lab
CFCM	Component based Fuzzy c-Means
CLT	Cognitive load theory
ECG	Electrocardiogram
EEG	Electroencephalography
EMG	Electromyography
ER	Emotion recognition
fNIRS	Functional near-infrared spectroscopy
GPU	Graphics processing unit
GSR	Galvanic Skin Response
HB	Hemoglobin
HRV	Heart rate variability
MET	Multiple Errands Test
REC	Regression Error Characteristic
TPU	Thermoplastic polyurethane

CHAPTER 1

INTRODUCTION

Through scalp-mounted electrodes, an EEG measures the electrical activity of your brain. In particular, epilepsy and other seizure disorders may be identified using the EEG data, which represent anomalies in brain activity.

A corporation named BIOPAC manufactures data collection equipment that may be used to assess physiological data such as heart rate, electrocardiograms, grip strength, and other physiological phenomena. To assess and examine data on weariness, the EEG model is applied. Drivers need to concentrate their focus on the traffic condition in order to guarantee the safety of their driving activities .

Despite the fact that drivers are neither sleep deprived nor in boring or low load settings, research have demonstrated that these variables lead to symptoms of tiredness and reduced driving abilities. or fatigued, driving-related duties are a cause of weariness. It is referred to as passive weariness.

Causes of passive exhaustion through nerve habituation, such as by continuously driving on routes that are regularly utilised , as contrasted to the driver's active weariness brought on by an irregular circadian cycle and lack of sleep . Fell and Black performed research on accidents connected to driver sleepiness in Sydney, which encompassed all fatigue-related events.

It was also observed that 45% of collision drivers As a consequence, the present study's purpose is to analyse the HRV and EEG power spectrum in chess players who compete against a computer and on a board. Additionally, we also want to look at the influence of exposure to chess. HRV and EEG power spectrums are measured by computers.

An electroencephalogram (EEG) is a test that measures electrical activity in the brain using small, metal discs (electrodes) attached to the scalp. Brain cells communicate via electrical impulses and are active all the time, even during asleep. This activity shows up as wavy lines on an EEG recording. An EEG is one of the main diagnostic tests for epilepsy.

1.1 Types of EEG tests for brain wave

A doctor may order a standard EEG test if a patient is experiencing symptoms such as persistent headaches, unexplained seizures, or behavioural changes.

Results from these tests are used to check for any abnormal brain waves that may be an indication of more serious underlying health conditions. Further tests may be required to make a diagnosis if an abnormality is found or detected.

A Standard EEG test is usually done on an outpatient basis at a hospital or clinic. The whole process may take up to two hours with the actual recording taking as little as 20 minutes. After which the patient is free to go back home.

If the patient is being reevaluated, then the doctor may ask them to stop taking currently prescribed medications a day before the test. This is done so that whatever abnormal symptoms that the patient was being treated for can be reevaluated during the test.

1.1.1 Sleep EEG test

When a person is sleeping, the brain wave activity is different from the awake state and some types of abnormal waves are more easily detected when the patient is sleeping.

Sometimes seizures happen when the patient is asleep. Sleep EEG tests are done very much like standard EEG tests with the only exception being the patient will be asleep during the test.

Patients having difficulty relaxing and falling asleep may be given medications to assist in falling asleep. In such cases, patients may need assistance in returning home or need to stay back for a few extra hours at the hospital.

1.1. 2 Sleep-deprived EEG test

A Sleep-deprived EEG test is similar to the Sleep EEG tests but the patient is asked to deprive themselves of sleep. It is a test done to improve the possibility of detection of abnormal brain wave activities. The possibility of detecting abnormal brain waves is also much higher when the patient does not have enough sleep or is tired. In

preparation for this test, the patient may be asked to stay awake the previous night or get up earlier than usual. The test is usually conducted in the morning and all caffeine should be completely avoided before a test is given.

1.1.3 Ambulatory EEG test

When a patient is experiencing unexplained seizure episodes at random intervals these episodes become very difficult to predict and if all previous tests failed to capture a seizure episode, an Ambulatory EEG test is prescribed.

Ambulatory EEG is a test similar to the standard EEG test in the type of information it records, with the added benefit that the patient can be mobile and is not confined to the testing centre. Ambulatory means being able to walk.

This EEG test device uses similar electrodes to a standard EEG test; however, they are all connected to a self-contained compact recording device that can be carried around like a previous-generation portable radio.

The patient is free to go through their daily routine while the device continuously records all brain wave activities. The test period can range from a few hours to a few days.

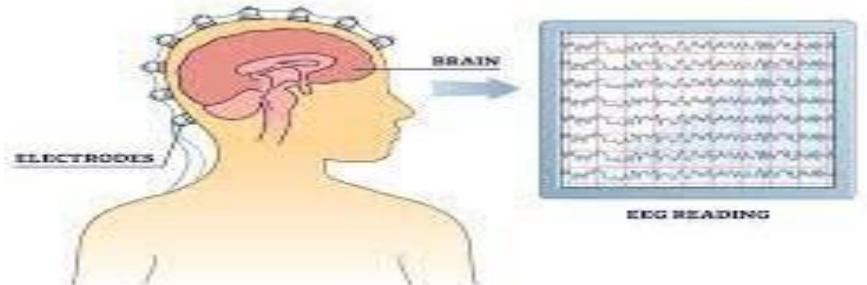
The patient is asked to keep a record of all their activities during the test period. The patient will also need an assistant who can watch them during the test period in case a seizure occurs. The assistant will be able to record helpful details about the incident.

1.1.4 Neurofeedback EEG test

Neurofeedback, also known as EEG biofeedback, is a kind of brain training activity done with the help of an EEG machine. This procedure is designed to alter and improve the brainwave activity, thereby helping the patient overcome undesirable conditions like depression, anxiety, eating disorders, etc.

Children suffering from attention deficit hyperactivity disorder(ADHD) can also benefit greatly from this procedure. After the testing phase is completed, the doctor can compare the written records with actual brain wave data

(electroencephalogram) and get a clearer understanding of what was happening during a seizure episode.



**Fig.1.1 Electroencephalogram (courtesy-
<https://www.simplypsychology.org/what-is-an-eeeg.html>)**

1.2 BLOOMS TAXONOMY

Bloom's taxonomy is a set of three hierarchical models used for the classification of educational learning objectives into levels of complexity and specificity. The three lists cover the learning objectives in cognitive, affective, and psychomotor domains. The cognitive domain list has been the primary focus of most traditional education and is frequently used to structure curriculum learning objectives, assessments, and activities

The models were named after Benjamin Bloom, who chaired the committee of educators that devised the taxonomy. He also edited the first volume of the standard text, *Taxonomy of Educational Objectives: The Classification of Educational Goals*

The goal of educator's using Bloom's taxonomy is to encourage higher-order thinking in their students by building up from lower-level cognitive skills. Behavioural and cognitive learning outcomes are given to highlight how Bloom's taxonomy can be incorporated into larger-scale educational goals or guidelines. The key phrases

can be used (e.g., Example Assessments) to prompt for these skills during the assessment process). The terminology has been recently updated to include the

following six levels of learning. These 6 levels can be used to structure the learning outcomes, lessons, and assessments of your course.

Remembering: Retrieving, recognizing, and recalling relevant knowledge from long-term memory.

Understanding: Constructing meaning from oral, written, and graphic messages through interpreting, exemplifying, classifying, summarizing, inferring, comparing, and explaining.

Applying: Carrying out or using a procedure for executing, or implementing.

Analyzing: Breaking material into constituent parts, and determining how the parts relate to one another and an overall structure or purpose through differentiating, organizing, and attributing.

Evaluating: Making judgments based on criteria and standards through checking and critiquing.

Creating: Putting elements together to form a coherent or functional whole; reorganizing elements into a new pattern or structure through generating, planning, or producing.

Like other taxonomies, Bloom's is hierarchical, meaning that learning at the higher levels is dependent on having attained prerequisite knowledge and skills at lower levels. You will see Bloom's Taxonomy often displayed as a pyramid graphic to help demonstrate this hierarchy. We have updated this pyramid into a "cake-style" hierarchy to emphasize that each level is built on a foundation of the previous levels.

Bloom's taxonomy is a powerful tool to help develop learning outcomes because it explains the process of learning:

Before you can understand a concept, you must remember it.

- To apply a concept, you must first understand it.

- To evaluate a process, you must have analyzed it.
- To create an accurate conclusion, you must have completed a thorough evaluation



Fig.1.2. Blooms Taxonomy (courtesy-[Using Bloom's Taxonomy to Write Effective Learning Outcomes | Teaching Innovation and Pedagogical Support \(uark.edu\)](#))

CHAPTER 2

LITERATURE SURVEY

Juan Pedro Fuentes Garcia (2019) The aim of the present study was to investigate how the heart and the brain react to playing chess with a computer versus in a real context in chess players. we also aim to investigate if familiarization with simulated practice leads to changes in heart rate variability (HRV) and the electroencephalographic (EEG) power spectrum.

Jingzhou guo. (2014) Depression is a common mental health illness worldwide that affects our quality of life and ability to work . Although prior research has used EEG signals to increase the accuracy to identify depression ,the rates of underdiagnosis remain high and novel methods are required to identify depression . The results showed that our model is an effective means to identify state depression. This study demonstrates that using the model, people with state depression could be identified in a timely manner and receive interventions or treatments, which may be helpful for the early detection of depression.

Setha Pan-ngum. (2019) Future healthcare applications which are increasingly moving towards out-of- hospital or home-based caring models , the ability to remotely and continuously monitor patient's conditions effectively are imperative . All aspects of the designs, engineering, and experimenting by applying machine learning for emotion classification, are covered. These results, together with its earphone-like wearability, suggest its potential usage especially for future healthcare applications, such as home-based or tele-monitoring systems as intended.

Brinkman k (2022) Autonomous sensory meridian response (ASMR) is a sensory and emotional phenomenon , characterized by the experience of a “tingling”. static-like sensation, which is generally called paraesthesia . The observed ASMR-induced decrease of alpha and theta power and increase of beta power and (only in low conscientious participants) EDA may reflect that, apart from relaxation .

Lukasz D.Kaczmarek (2022) The Emotion recognition dataset is dedicated to testing methods for emotion recognition (ER) from physiological response and facial expressions. This work reviews progress in sensors and machine learning methods and techniques that have made it possible to move ER from the lab to the field in recent years. The review is concluded with a debate on what challenges need to be overcome in the domain in the near future.

Chatterjee Debatri, *et al.*, (2013) This process aims at designing a novel scheme for cognitive load classification of subjects engaged in program analysis. The logic of propositions has been employed here to construct program segments to be used for cognitive load analysis and classification. Electroencephalogram signals acquired from the subjects during program analysis are first fuzzified and the resultant fuzzy membership functions are then submitted to the input of a fuzzy rule-based classifier to determine the class of the cognitive load of the subjects.

Sinharay Arijit, *et al.*, (2013) The paper aims at evaluation of different onscreen keyboard layouts based on the biological responses of the users. The signal used for the said purpose is Electroencephalogram acquired by low-cost neuro-headset from Emotiv(causing strong feeling). We propose to use human cognition as the fundamental feature to discriminate between user-friendly vs. cumbersome onscreen layout designs.

E. Molteniet (2009) We evaluated frontal brain activation during a working memory task with graded levels of difficulty in a group of 19 healthy subjects, by means of time-resolved fNIRS technique .Functional near-infrared spectroscopy (fNIRS) is a noninvasive optical imaging technique that measures changes in oxygenated and deoxygenated hemoglobin (Hb) concentrations within the brain by means of their characteristic absorption spectra of the wavelengths range of 700–1000 nm

F. Paas, *et al.*, (2003) In this article, we discuss cognitive load measurement techniques with regard to their contribution to cognitive load theory (CLT). CLT is concerned with the design of instructional methods that efficiently use people's limited cognitive processing capacity to apply acquired knowledge and skills to new situations (i.e., transfer). CLT is based on a cognitive architecture that consists of a limited working memory with partly which interacts with an unlimited long-term

memory. These structures and functions of human cognitive architecture have been used to design a variety of novel efficient instructional methods.

N. Alderman, *et al.*, (2003) Reported the utility of the Multiple Errands Test (MET) in discriminating executive deficits in three frontal lobe patients with preserved high IQ, who were otherwise unimpaired on tests of executive function. This pattern was strongly associated with observed dysexecutive symptoms in everyday life. The results demonstrate the clinical utility of the test, and suggest that there are two common and independent sources of failure on multitasking tests in a general neurological population: memory dysfunction, and initiation problems.

T. Lan, *et al.*, (2005) Using EEG signals to estimate cognitive state has drawn increasing attention in recently years, especially in the context of brain-computer interface (BCI) design. However, this goal is extremely difficult because, in addition to the complex relationships between the cognitive state and EEG signals that yields the non-stationarity of the features extracted from EEG signals, there are artefacts introduced by eye blinks and head and body motion. In this paper, we present a classification system, which can estimate the subject's cognitive state .

P. Antonenko, *et al.*, (2010) Application of physiological methods, in particular electroencephalography (EEG), offers new and promising approaches to educational psychology research .This paper presents a review of seminal literature on the use of continuous EEG to measure cognitive load and describes two case studies on learning from hypertext and multimedia that employed EEG methodology to collect and analyze cognitive load data.

Scholler Simon, *et al.*, (2012) An approach to the direct measurement of perception of video quality change using electroencephalography (EEG) is presented. Subjects viewed 8-s video clips while their brain activity was registered using EEG. The video signal was either uncompressed at full length or changed from uncompressed to a lower quality level at a random time point. Potentially, a neurotechnological approach to video assessment could lead to a more objective quantification of quality change detection, overcoming the limitations of subjective approaches.

Furthermore, it allows for real-time applications wherein the brain response to a video clip is monitored while it is being viewed.

Yuan Yueran, *et al.*, (2014) Assessment of reading comprehension can be costly and obtrusive. In this paper, we use inexpensive EEG to detect reading comprehension of readers in a school environment. We use EEG signals to produce above-chance predictors of student performance on end-of-sentence close questions. We also attempt to distinguish the student mental states . In total, this work investigates the practicality of classroom use of inexpensive EEG devices as an measure of reading comprehension.

Nourbakhsh Nargess *et al.*, (2012) Galvanic Skin Response (GSR) has recently discovered that attention as a prospective physiological indicator of cognitive load and emotions. Obtained results show the strong significance of the explored features, especially the spectral ones, in cognitive workload .

Anderson W Erik *et al.*, (2011) Effectively evaluating visualization techniques is a difficult task often assessed through feedback from user studies and expert evaluations. This work presents an alternative approach to visualization evaluation in which brain activity is passively recorded using electroencephalography (EEG). The design of the user study performed, the extraction of cognitive load measures from EEG data, and how those measures are used to quantitatively evaluate the effectiveness of visualizations.

Das Diptesh, *et al.*, (2013) Individuals exhibit different levels of cognitive load for a given mental task. Measurement of cognitive load can enable real-time personalized content generation for distant learning, usability testing of applications on mobile devices and other areas related to human interactions. In the unsupervised domain, the Component based Fuzzy c-Means (CFCM) outperforms the traditional Fuzzy c-Means (FCM) in terms of the measurement accuracy of the cognitive load.

Brian Kim, *et al.*, (2023) EEG phase is increasingly used in cognitive neuroscience, brain-computer interfaces, and closed- loop stimulation devices. However, it is unknown how accurate EEG phase prediction is across cognitive states.

Ce Zhang and Azim Eskandarian (2021) The driver's cognitive and physiological states affect his/her ability to control the vehicle. Thus, these driver states are essential to the safety of automobiles. The design of advanced driver assistance systems (ADAS) or autonomous vehicles will depend on their ability to interact effectively with the driver.

Saeed Shadpour and Ambreen Shafqat (2023) Cognition, defined as the ability to learn, remember, sustain attention, make decisions, and solve problems, is essential in daily activities and in learning new skills. The purpose of this study was to develop cognitive workload and performance evaluation models using features that were extracted Electroencephalogram .

CHAPTER 3

AIM AND SCOPE

3.1 AIM

- To acquire EEG signals while solving 6 levels of Blooms taxonomy using BioPACK.
- To do statistical, spectral, and time frequency analysis of EEG during problem solving.
- To classify the signals using AI to characteristics the brain behavior for reasoning and problem solving.

3.2 SCOPE

- Analyzing EEG (Electroencephalography) during problem-solving tasks can provide valuable insights into cognitive processes and brain activity at different levels of Bloom's Taxonomy. Bloom's Taxonomy is a framework that classifies educational objectives and cognitive processes into six levels, ranging from lower-order thinking skills to higher-order thinking skills.
- Overall, EEG analysis during problem-solving tasks can reveal the timing and patterns of neural activity associated with different cognitive processes. It allows researchers to gain a deeper understanding of how individuals engage with problems at various levels of cognitive complexity according to Bloom's Taxonomy.
- This knowledge can have implications for education, psychology, and neuroscience, as it provides a window into the inner workings of the human mind during problem-solving.

3.3 BLOCK DIAGRAM

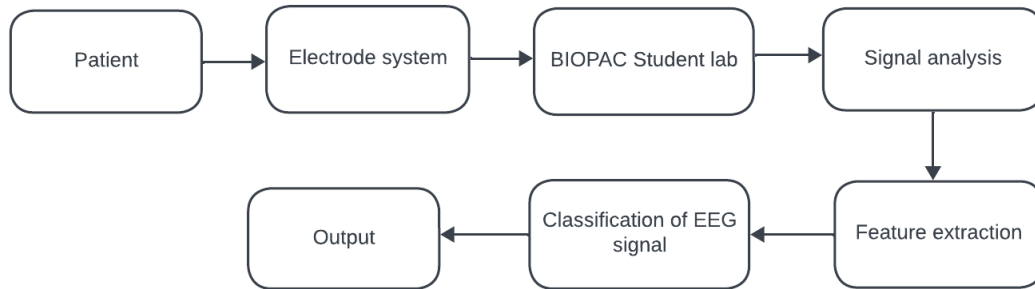


Fig 3.1 Block Diagram to asses EEG Signal using BIOPAC

CHAPTER 4

MATERIALS AND METHODS

4.1 INTRODUCTION

The electrodes and the lead selection circuits are connected to the BIOPAC. The leads are placed in the proper position as mentioned in the BIOPAC module.



Fig 4.1 ELECTRODES PLACEMENT

The white crab electrode which is said to negative is placed on the test sample's just right to the ears. The red crab electrode is positive and is placed above the ears of the sample. The black crab electrode is the ground and is placed on the bottom of the ears of the sample. All these crab electrodes are mounted on the sample's body with the help of surface gel electrodes.

4.2 BIOPAC Device

A flexible system created for data collecting and analysis in research and teaching is the BIOPAC MP45 Data collecting System. A variety of physiological signals, including ECG, EMG, and EEG, among others, can be measured using the MP45. A research-grade data acquisition device for recording and analyzing physiological data is called the BIOPAC MP45. It is a multi-channel system that has the capacity to simultaneously capture physiological data from up to 16 channels, making it an effective tool for numerous research applications. The MP45 data collection unit,

a compact, transportable device that can be linked to a computer through USB, is a component of the BIOPAC MP45 system. The Acknowledge software, which is used to record, analyze, and analyze data, is also part of the system. A robust set of tools for data analysis, including time-domain, frequency-domain, and non-linear analytic approaches, is offered by the Acknowledge software. For quick and effective data processing, the software also offers automated analysis choices and editable analysis templates.



Fig 4.2 BIOPAC MP45

4.3 BSL BIOPAC STUDENT LAB SOFTWARE

A software called BSL (BIOPAC Student Lab) was created by BIOPAC with the purpose of being used in educational settings to teach physiological concepts and carry out laboratory investigations. Because of the software's user-friendly and intuitive design, even students with little to no physiology or data gathering experience can use it.

The BSL software also contains a variety of tools for data analysis and visualization, including time-domain analysis, frequency-domain analysis, and trend analysis, in addition to the pre-designed lab assignments. The software additionally enables modification of the channel, sample rate, and filter parameters used in data acquisition. The BSL software is a flexible and adaptable tool for physiology instruction since it works with a variety of BIOPAC data gathering systems and

sensors. It is a useful tool for both students and teachers and are utilized in educational institutions all over the world, from high schools to colleges.

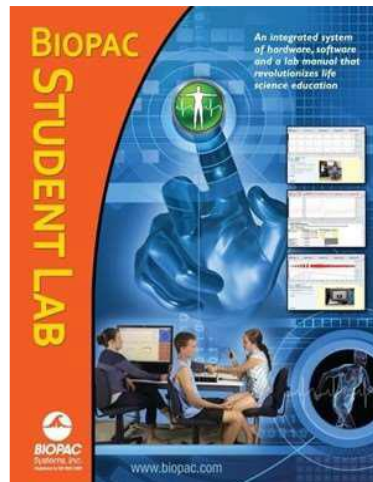


Fig 4.3 BIOPAC Student lab software

4.4 SURFACE GEL ELECTRODES

Electrodes which are used to evaluate the autonomic nervous system and, can also be recorded using surface gel electrodes. Surface gel electrodes are adhered to the skin with conductive gel or glue in order to record active brain signals. After the electrodes are connected, a BIOPAC data acquisition device records the EEG signals and uses specialized software to analyze the brain signals .

Time-domain and frequency-domain analysis are frequently used in brain signals study, and both techniques can reveal information regarding the activity of the parasympathetic and sympathetic branches of the autonomic nervous system. This data can be used to evaluate stress levels, cardiovascular health, and general wellbeing. Overall, BIOPAC surface gel electrodes provide a practical and dependable solution for physiological data collection and analysis. These electrodes can be utilized for a wide range of physiological signals. Surface gel electrodes are non-invasive, simple to use, and commonly used for brain signals monitoring.



Fig 4.4 Surface gel electrodes

4.5 LEAD SELECTION CIRCUIT

With BIOPAC MP45 data collecting devices, a certain kind of shielded lead is referred to as a "SS2LB." The BIOPAC MP45 system's essential component, SS2LB shielded lead, enables the precise and dependable recording of physiological data in a range of research applications.

It is a fully insulated cable assembly that enables high resolution biopotential recording utilizing disposable electrodes in series. Standard pinch connections are used to connect the 2-meter adaptor to surface electrodes. The BIOPAC Student Lab data acquisition (MP45) research unit and the SS2LB are interfaced.

The subject is covered by the leads, which have an end that resembles a crab pin, on the top surface of the surface electrodes that are adhered to the subject.



Fig 4.5 SS2LB – Lead selection circuit

4.6 SOFTWARE USED

4.6.1 GOOGLE COLAB

Google Colab, short for Google Collaboratory, is a cloud-based platform provided by Google that allows users to write and execute Python code in a browser-based environment, without requiring any setup or installation. It is particularly popular among researchers, educators, and data scientists for its ease of use, accessibility, and integration with Google Drive.

Access and Environment: Google Colab is accessible through any web browser, including Chrome, Firefox, Safari, etc. Users can access Colab using their Google account. Colab provides a Python environment that includes common libraries for data analysis, machine learning, and scientific computing pre-installed, such as NumPy, Pandas, Matplotlib, TensorFlow, PyTorch, etc.

Jupyter Notebooks: Google Colab is based on Jupyter Notebooks, which allow users to create and share documents that contain live code, equations, visualizations, and narrative text. Notebooks are organized into cells, which can contain either code or text (Markdown).

Free Cloud Computing: Google Colab provides free access to computing resources, including CPU, GPU, and TPU (Tensor Processing Unit). Users can select the type of hardware accelerator they need (GPU or TPU) for their notebooks. The free tier comes with certain limitations, such as maximum session duration and resource usage.

Integration with Google Drive: Colab integrates seamlessly with Google Drive, allowing users to create, save, and share their notebooks directly from Google Drive. Users can also import datasets and files from Google Drive into their Colab notebooks.

Collaboration Features: Multiple users can collaborate on the same notebook in real-time. Users can share their notebooks with others by providing them with a link or granting them access via email.

Interactive Data Visualization: Colab supports interactive data visualization using libraries like Matplotlib, Seaborn, Plotly, etc. Users can create interactive charts, graphs, and plots directly within their notebooks.

Markdown Support: Colab supports Markdown, allowing users to write formatted text, add headings, lists, links, images, etc., to provide explanations and documentation within their notebooks.

Code Execution and Output: Users can execute code cells individually or all at once. Output, including printed text, errors, and visualizations, is displayed directly below the code cell.

Persistent Storage: Colab provides temporary storage for notebooks and files, which is available for the duration of the session. Users can mount Google Drive for persistent storage across sessions.

Additional Features: Users can install additional Python libraries using pip directly within Colab notebooks. Colab provides access to external data sources and APIs for data retrieval and analysis. Advanced users can customize runtime settings, manage dependencies, and install system packages.

4.6.2. TO CREATE AND RUN

Step 1: Access Google Colab :

- Open your web browser and go to Google Colab.
- Sign in with your Google account if you're not already signed in.

Step 2: Create a New Notebook :

- Once you're logged in, you'll see the Colab dashboard.
- Click on the "New Notebook" button to create a new notebook.

- This will open a new untitled notebook where you can start writing your code.

Step 3: Create a New Notebook :

- Once you're logged in, you'll see the Colab dashboard.
- Click on the "New Notebook" button to create a new notebook.
- This will open a new untitled notebook where you can start writing your code.

Step 4: Write Python Code :

- In a code cell, you can write Python code just like you would in a local Python environment. Type or paste your Python code into the code cell.
- Type or paste your Python code into the code cell.

Step 5: Execute Code Cells :

- To execute a code cell, click on the play button (triangle icon) on the left side of the cell.
- Alternatively, you can use the keyboard shortcut "Shift + Enter" to execute the cell.
- When you run a code cell, Colab sends the code to Google's servers, executes it, and displays the output below the cell.

Step 6: Add Markdown Text :

- In a text cell, you can write documentation, explanations, and formatted text using Markdown syntax.
- Markdown allows you to add headings, lists, links, images, and more to your notebook.
- Write your text content using Markdown syntax in the text cell.

Step 7: Execute Markdown Cells :

- Text cells don't need to be executed like code cells.
- They are rendered immediately after you finish writing them.

Step 8: Save and Name Your Notebook :

- To save your notebook, click on "File" in the menu bar and then select "Save" or press "Ctrl + S" (Cmd + S on Mac).
- You can also give your notebook a meaningful name by clicking on "Untitled" at the top of the notebook and entering a name.

Step 9: Share and Collaborate :

- You can share your Colab notebook with others by clicking on the "Share" button at the top right corner of the notebook.
- You can share the notebook via link or invite collaborators by entering their email addresses.

4.7 PRE-PROCESSING :

Pre-processing data for the cognitive domain involves preparing and organizing data to ensure it is suitable for analysis and interpretation within the context of cognitive science or related fields. This process often includes various statistical calculations such as finding the mean, median, standard deviation, variance, skewness, and kurtosis of the data. Here's an explanation of each

Mean: The mean is the average value of a dataset and is calculated by summing all values in the dataset and dividing by the number of observations. It is a measure of central tendency and provides an overall idea of the dataset's typical value.

Median: The median is the middle value of a dataset when it is ordered from least to greatest. If there is an even number of observations, the median is the average of the two middle values. The median is also a measure of central tendency, but it is less affected by extreme values compared to the mean.

Standard Deviation: The standard deviation measures the dispersion or spread of values in a dataset relative to the mean. It indicates the average deviation of each

data point from the mean. A high standard deviation suggests that the data points are spread out over a wider range, while a low standard deviation indicates that the data points are closer to the mean.

Variance: The variance is the squared value of the standard deviation. It measures the average squared deviation of each data point from the mean. Like the standard deviation, it provides a measure of the spread of data points around the mean.

Skewness: Skewness measures the asymmetry of the distribution of values in a dataset. A skewness value of zero indicates a symmetrical distribution, where the mean, median, and mode is all equal. Positive skewness indicates that the tail of the distribution is longer on the right side, while negative skewness indicates a longer tail on the left side.

Kurtosis: Kurtosis measures the peaked ness or flatness of the distribution of values in a dataset compared to a normal distribution. A kurtosis value of zero indicates a normal distribution. Positive kurtosis (leptokurtic) indicates a distribution with heavier tails and a sharper peak, while negative kurtosis (platykurtic) indicates a distribution with lighter tails and a flatter peak.

SI.NO	NAME	MEAN	MEDIAN	SD	VARIANCE	SKEWNESS	KURTOSIS
1	AAKASH	1.000979386	-0.0201398	48.07146445	2310.865695	44.78736327	2078.336896
2	ABHISEK	0.998930005	-0.00036289	101.6858636	10340.01486	101.6954352	10341.97436
3	ANAND BALAJI	0.999592512	-0.000578267	58.31284471	3400.387858	58.31669609	3401.22432
4	ANGELIN	1.015223767	0.03735245	57.15815492	3267.054674	56.43934383	3206.17497
5	ANNIE	0.987857282	-0.01341095	48.38020555	2340.644289	47.0628605	2245.989446
6	BAVADHARANI	1.00235775	0.00337119	47.42609341	2249.234336	47.39493204	2247.517555
7	DILIP	0.998379115	-0.003618505	62.33122098	3885.181108	61.7329387	3829.879232
8	DINESH	1.002831416	0.0207087	44.59188518	1988.436224	44.23611104	1965.18035
9	DIVIYA	1.00800685	-0.008370595	36.49998674	1332.249032	36.51303061	1333.466567
10	ESDHWAR	0.964636811	0.01405765	48.40615945	2343.156273	46.32192374	2195.028107

Table 4.1 Pre-processing data of the student

In the context of cognitive science, these statistical measures help researchers understand the characteristics of data collected from experiments, surveys, or

observations. They provide insights into the central tendency, variability, and shape of the data distribution, which are essential for making inferences and drawing conclusions about cognitive processes, behaviors, and phenomena. Pre-processing data by calculating these statistics allows researchers to identify patterns, detect outliers, and prepare the data for further analysis using various statistical techniques and cognitive models.

CHAPTER 5

RESULT AND DISCUSSION

5.1. INTRODUCTION

The components are connected as shown in the block diagram and the data acquisition is done. The BIOPAC then generates the corresponding waveform for the test sample. Then this waveform is processed using the BSL software and the sympathetic vagal balance for the individual is acquired with its help. Now this value gives us an insight about the test sample's cognitive ability. The values are then classified according to the test sample's ages.

5.2 TESTING PROCEDURE

All the required components are tested and calibrated. The subject is explained about the process clearly. The test sample is made to be at ease while the recording takes place. The subject is said to be still in order to avoid any kind of artifacts that may occur during the recording procedure. The subject is also said to be calm and composed for convenient detection of the brain signal variability. The subject is given few questionnaires and is asked to answer the questions accordingly.

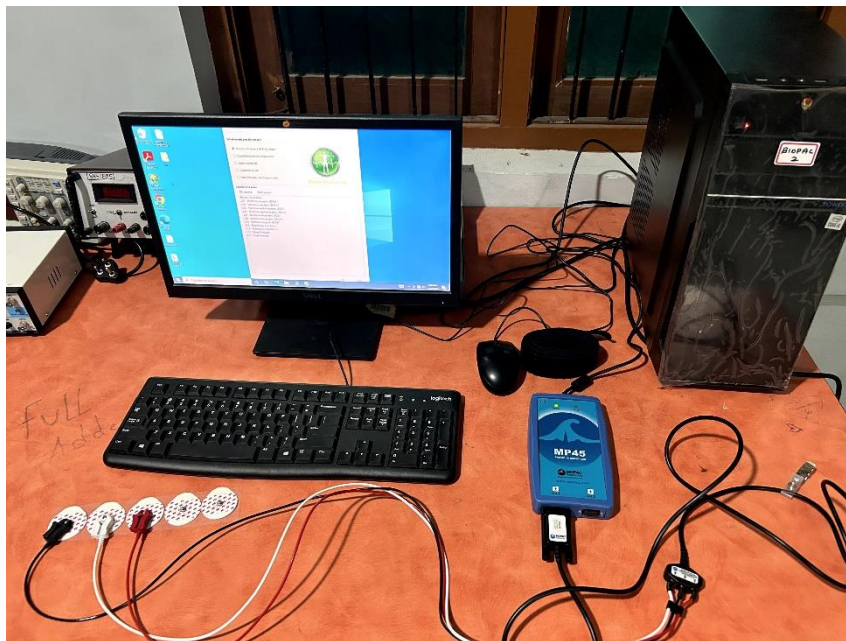


Fig 5.1 BIOPAC Module setup

5.3 EEG VALUE ANALYSIS

The appropriate steps are conducted in order to compute the individual's EEG signal values. The brain signals values for 40 participants have been taken into account in this study. For the assessment of brain signal values, nearly six series of measurements were taken. Under specific requirements, the subjects must complete a limited number of cognitive tasks ,in order to obtain the all three readings of the brain signal values. There were several questions that the participant had to respond to as part of the cognitive tasks including the level of difficulties (lower , Moderate ,Advance). The questionnaires had questions that tested respondents' aptitude question , spatial perception, and general knowledge. The BSL Software is then used to analyze the EEG signals.



Fig 5.2 EEG Analysis procedure

5.4 RESULT:

5.4.1 Alpha 1 (Lower level)

Train Accuracy – 95.93%

Test Accuracy – 94.18%

Validation accuracy – 94.06%

AUC – 97.69%

Loss – 0.0861

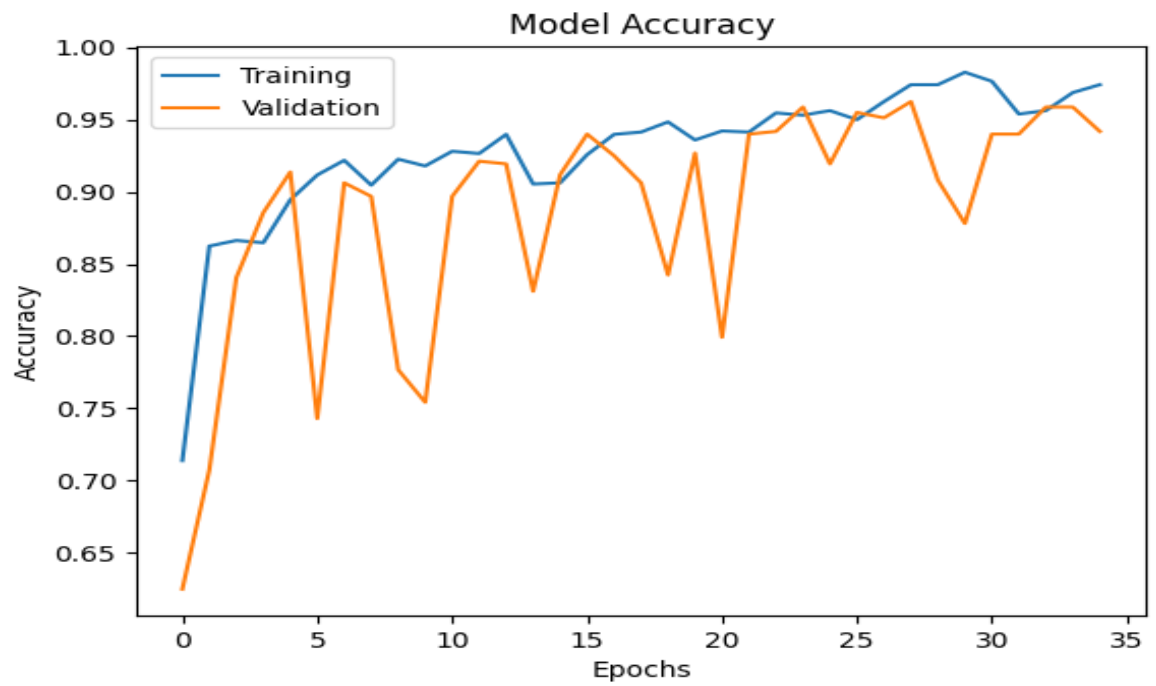


Figure 5.3 Model accuracy of lower level

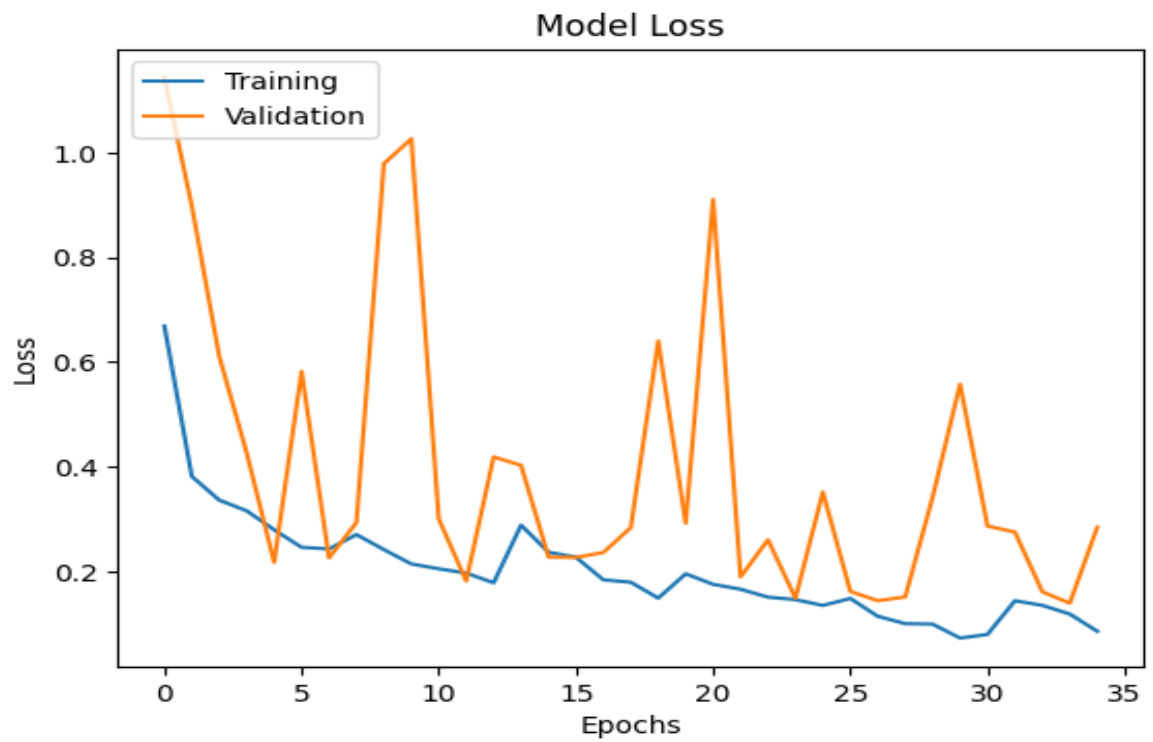


Figure 5.4 model loss of lower level

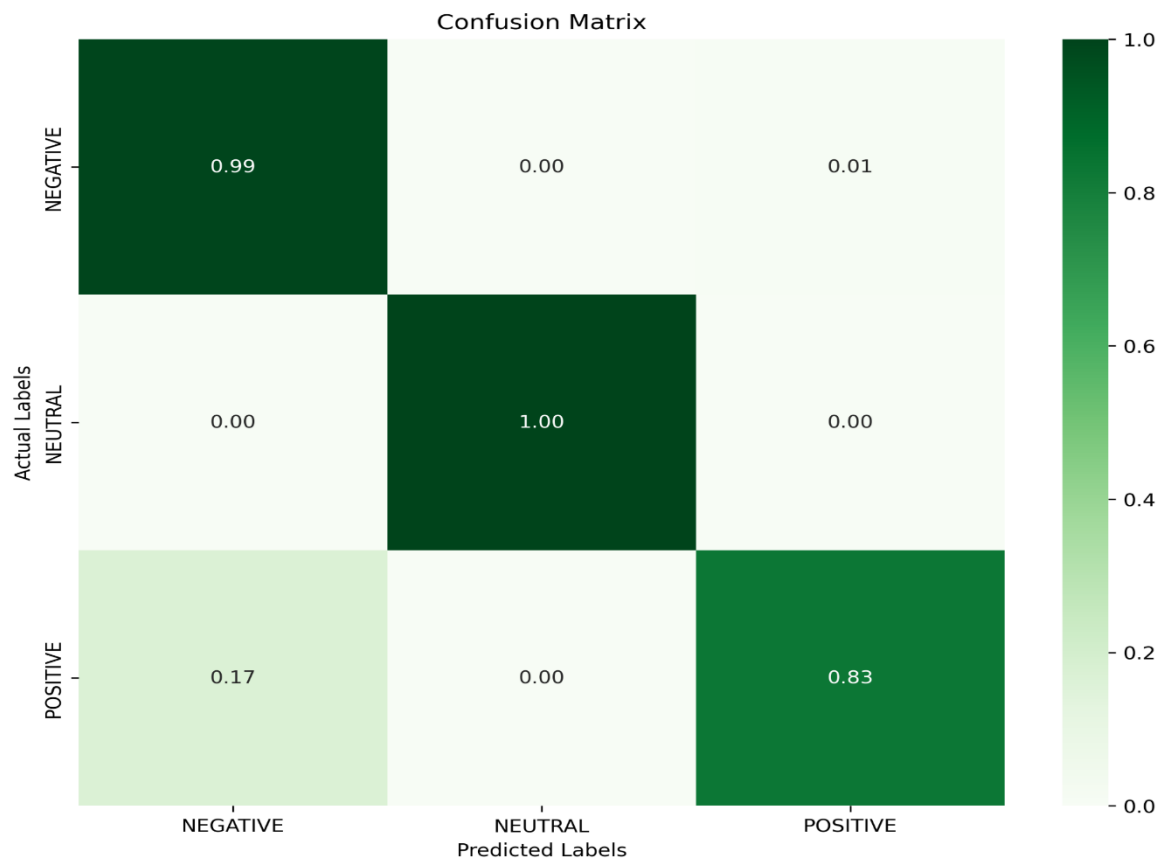


Figure 5.5 confusion matrix of lower level

5.4.2 Alpha 3 (Moderate level)

Train Accuracy – 96.20%

Test Accuracy – 94.93%

Validation accuracy – 95.31%

AUC – 98.68%

Loss – 0.0921

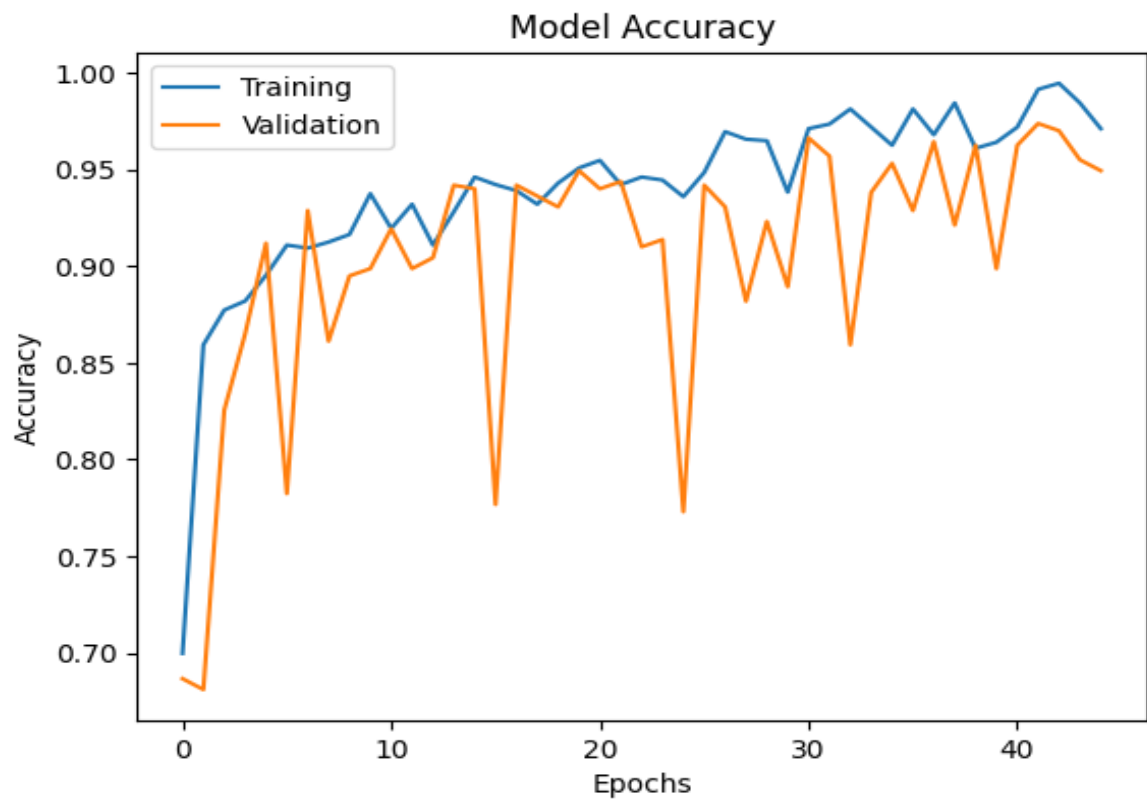


Figure 5.6 Model accuracy of moderate level

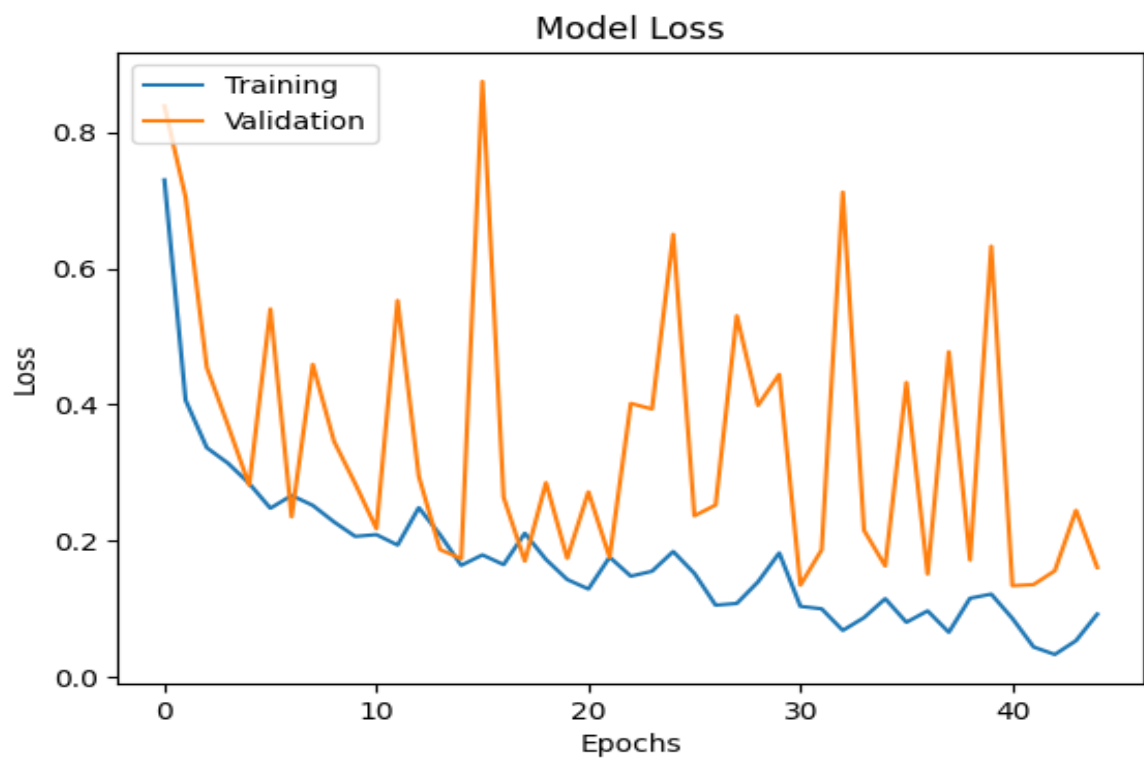


Figure 5.7 model loss of moderate level

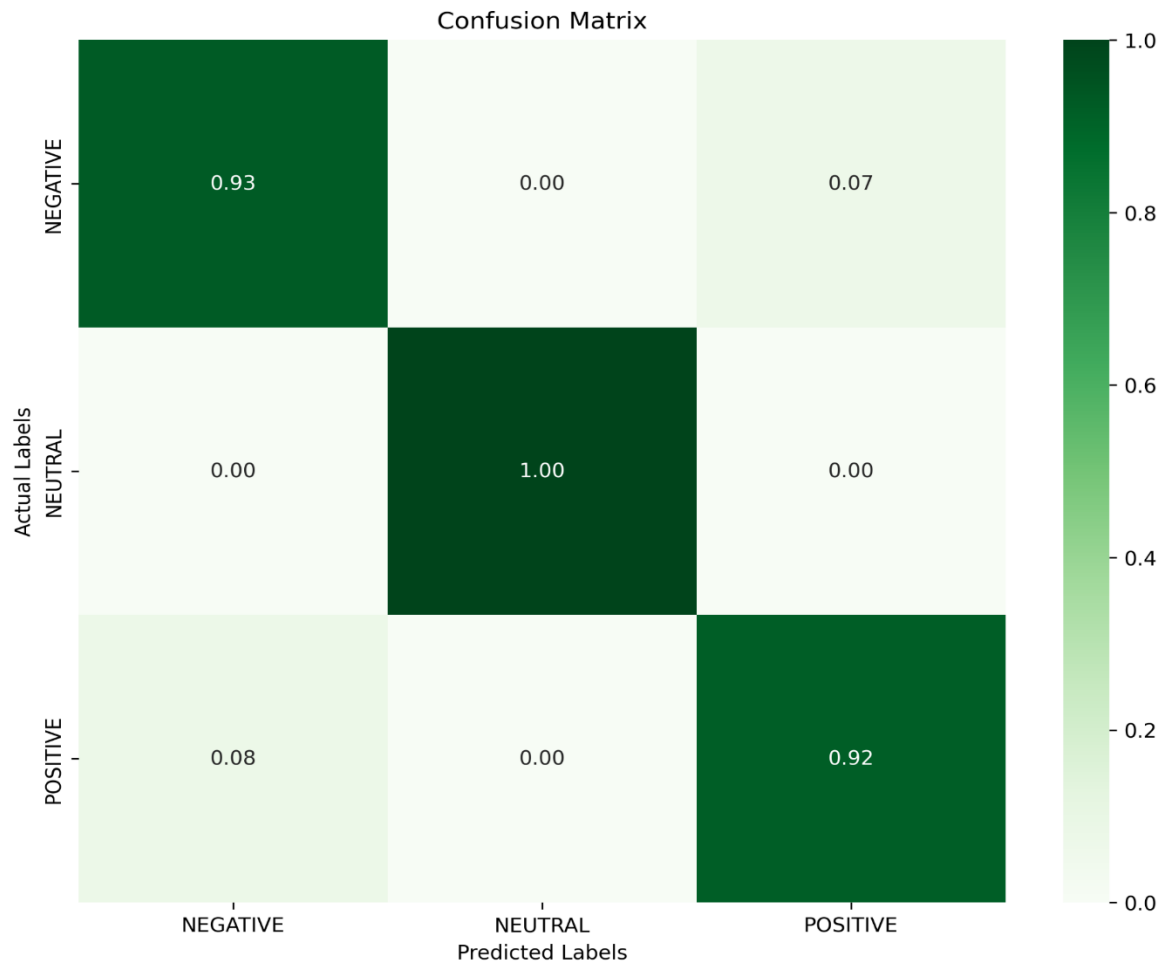


Figure 5.8 confusion matrix of moderate level

5.4.3 Alpha 6 (Advance level)

Train Accuracy – 97.89%

Test Accuracy – 96.24%

Validation accuracy – 95.00%

AUC – 97.90%

Loss – 0.0560

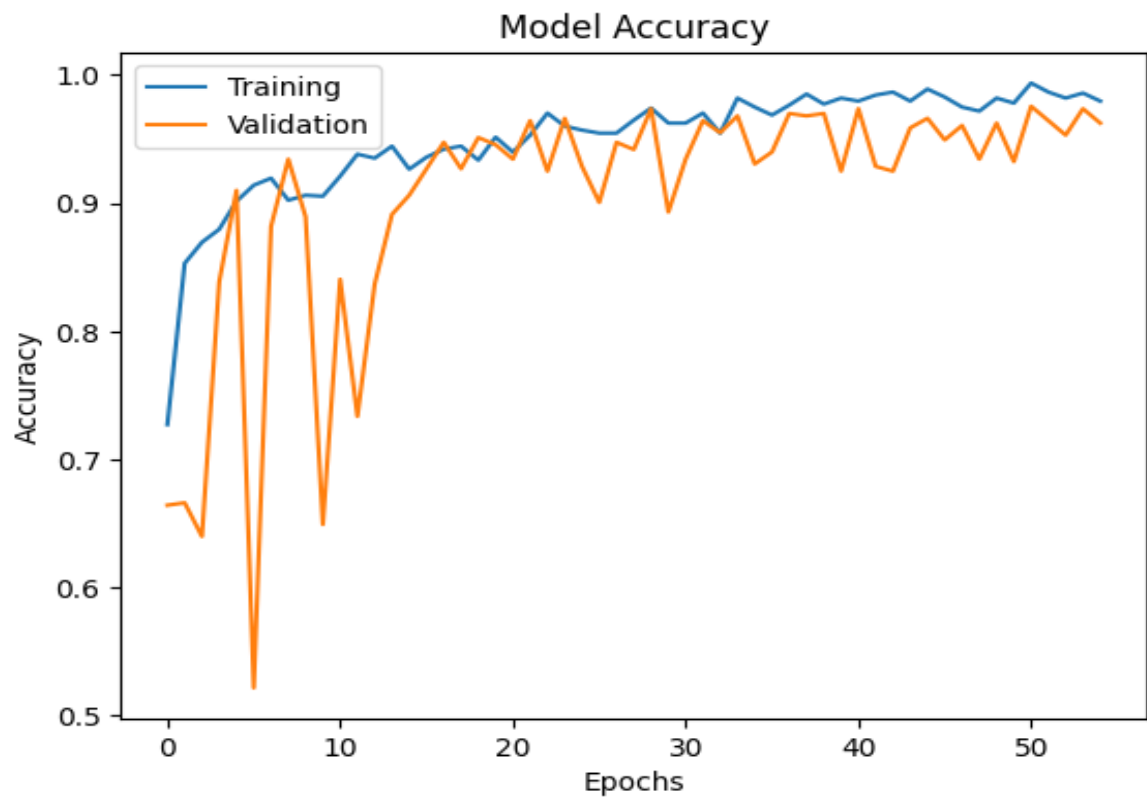


Figure 5.9 Model accuracy of advance level

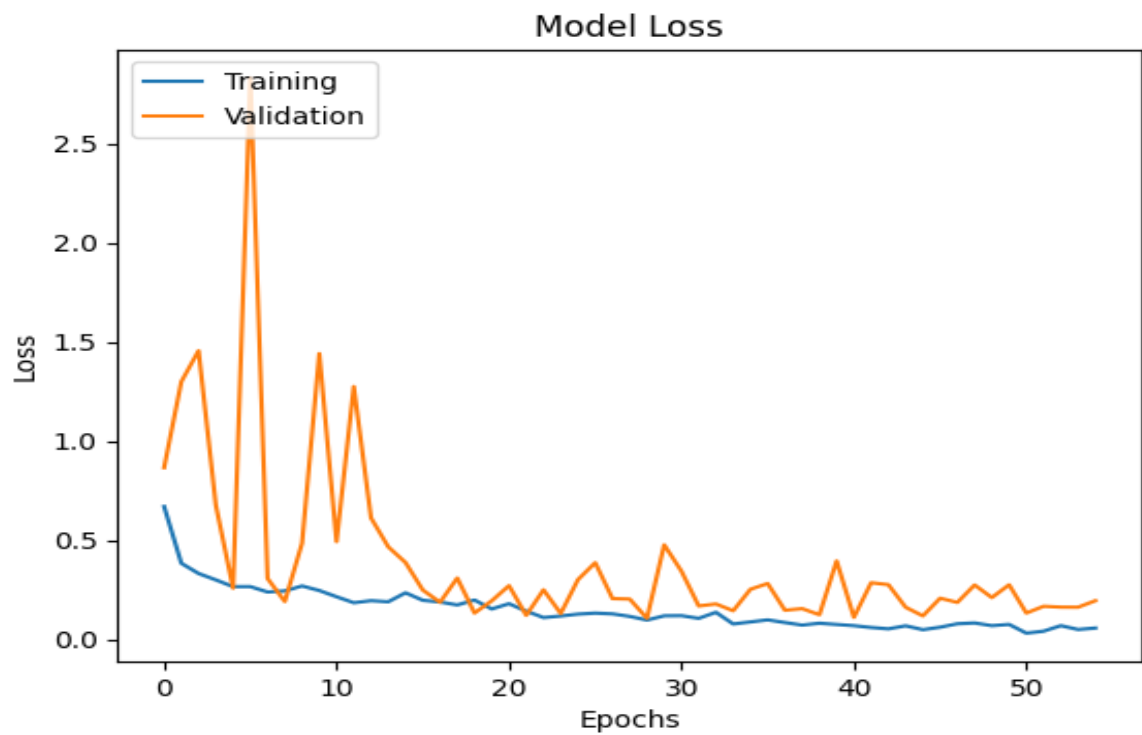


Figure 5.10 Model loss of advance level

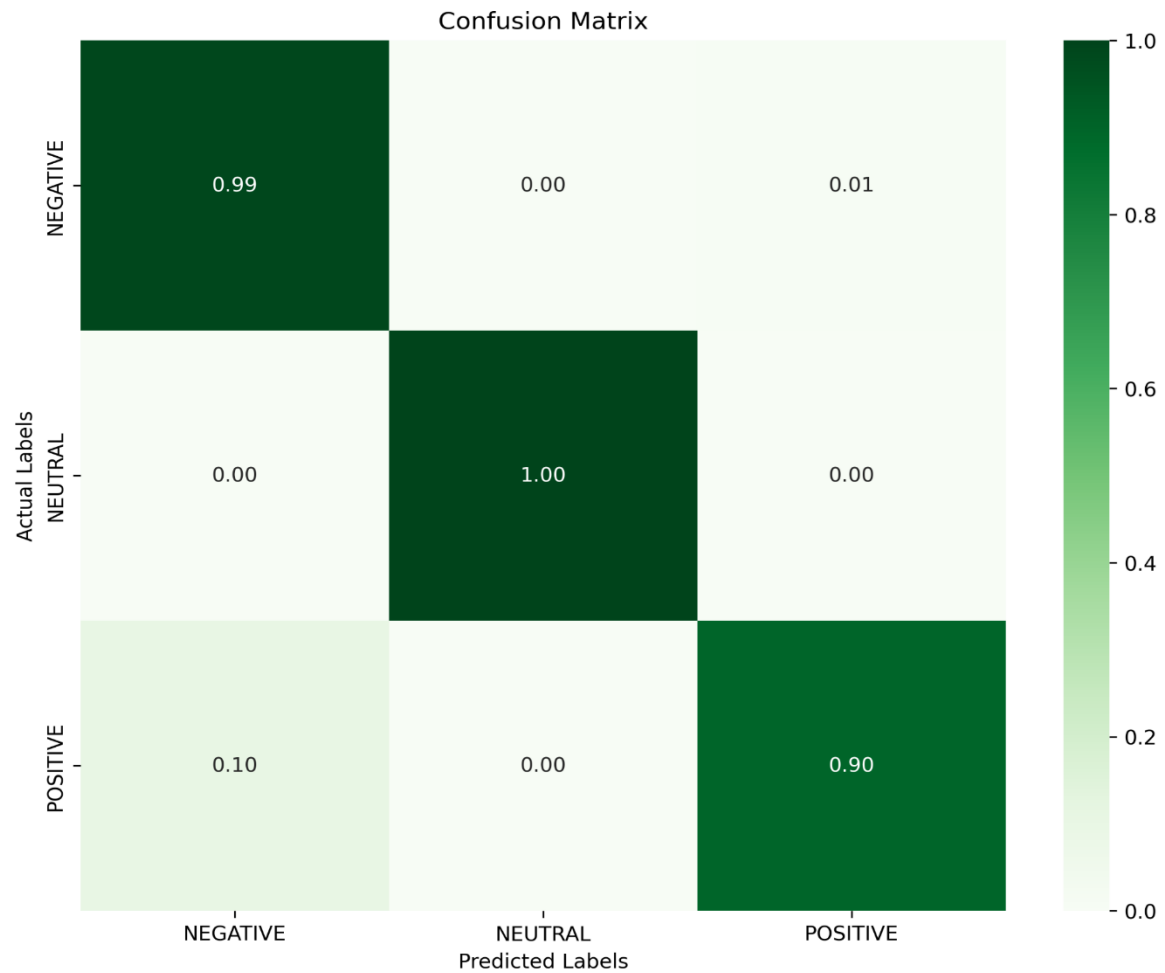


Figure 5.11 Confusion matrix of advance level

5.4.4 Alpha 1+3+6 (All Level)

Train Accuracy – 98.94%

Test Accuracy – 96.30%

Validation accuracy – 96.75%

AUC – 99.76%

Loss – 0.0765

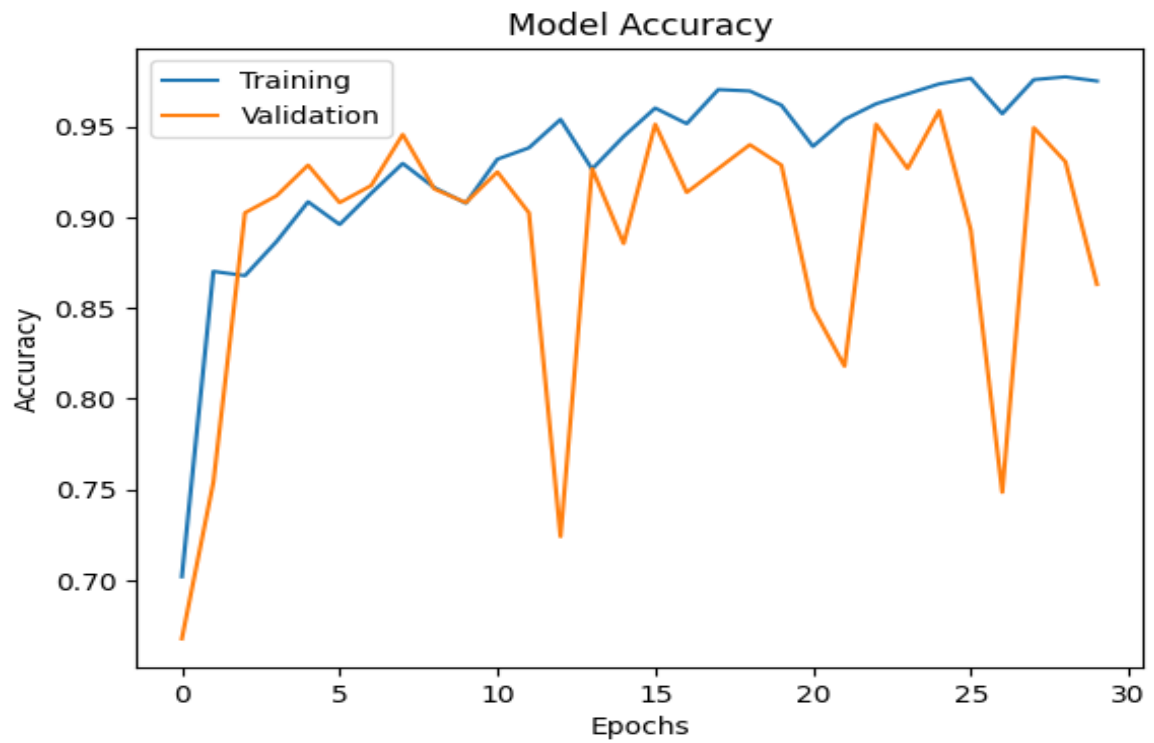


Figure 5.12 Model accuracy of all three level



Figure 5.13 Model loss of all three level

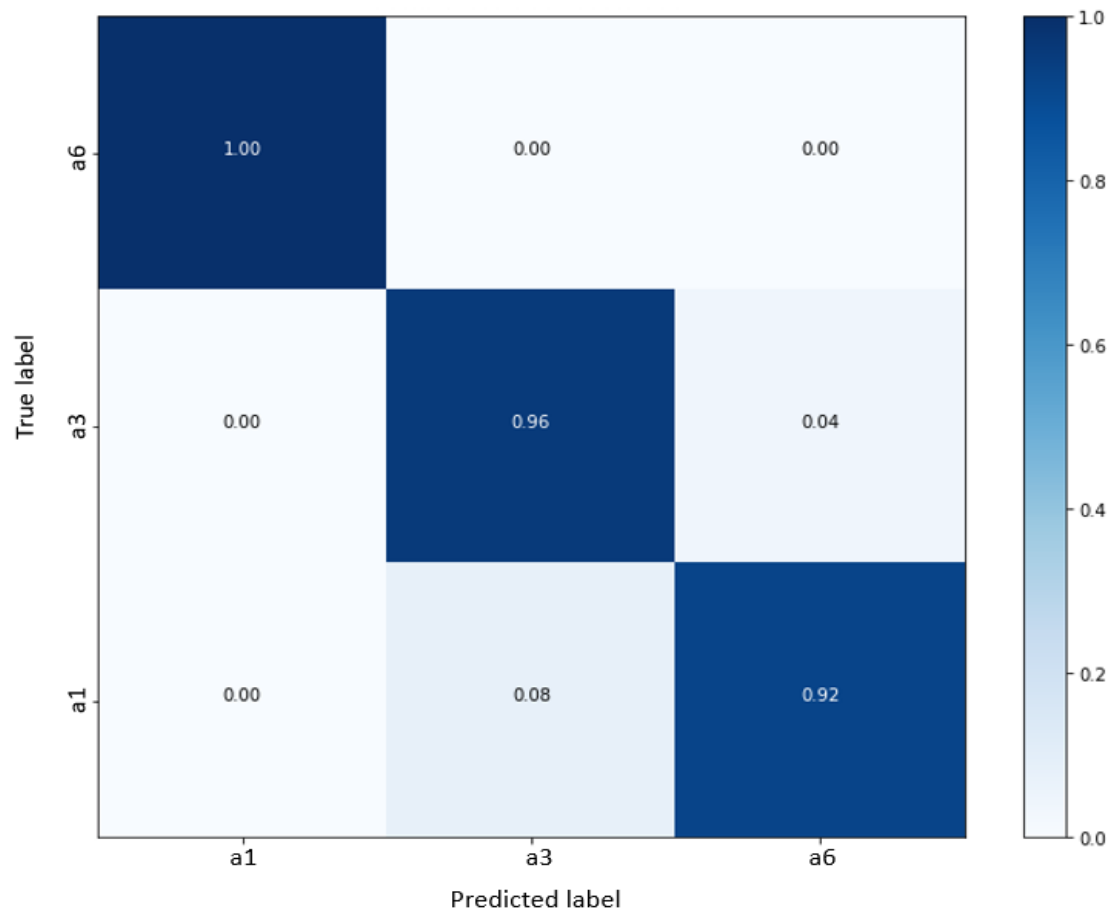


Figure 5.14 Confusion matrix of all three level

Overall result:

Alpha	Train Accuracy (%)	Test Accuracy (%)	Validation Accuracy (%)	AUC (%)	F1 score (%)	Precision (%)	Recall (%)	Loss
1	95.93	94.18	94.06	97.69	94	95	94	0.0861
3	96.20	94.93	95.31	98.68	95	95	95	0.0921
6	97.89	96.24	95.00	97.90	96	96	96	0.0560
1+3+6	98.94	96.30	96.75	99.76	97	97	97	0.0765

Table 5.1 Overall result

Understanding Bloom's Taxonomy:

Bloom's Taxonomy is a hierarchical framework used to classify educational learning objectives into levels of complexity and specificity. It consists of six levels: Remembering, Understanding, Applying, Analyzing, Evaluating, and Creating. These levels progress from lower-order thinking skills (Remembering and Understanding) to higher-order thinking skills (Applying, Analyzing, Evaluating, and Creating).

Interpretation of Accuracy Rates:

High Accuracy Rate in Advanced Level (Analyzing, Evaluating, Creating):

Advanced level questions typically require higher-order cognitive skills such as analysis, evaluation, and creation. Respondents who achieve a high accuracy rate in these questions demonstrate proficiency in critical thinking, problem-solving, and synthesizing information. They can analyze complex scenarios, evaluate multiple perspectives, and create innovative solutions. This high accuracy rate suggests that test-takers have a solid grasp of advanced concepts and can effectively apply them in novel situations.

Medium Accuracy Rate in Moderate Level (Applying):

Moderate level questions usually involve applying concepts and principles to solve problems or complete tasks. While respondents may not demonstrate the same level of proficiency as with advanced level questions, the moderate accuracy rate indicates a reasonable ability to apply learned knowledge. Test-takers are able to use acquired information to solve problems within familiar contexts. However, they may encounter challenges when faced with more complex or abstract scenarios, leading to a slightly lower accuracy rate compared to advanced level questions.

Low Accuracy Rate in Lower Level (Remembering, Understanding):

Lower-level questions typically focus on remembering and understanding basic facts, concepts, and principles. Despite being the foundation of learning, these questions require lower-order cognitive skills and may not fully assess deeper understanding or critical thinking. The low accuracy rate suggests that respondents

struggle with recalling information or comprehending basic concepts. This could be due to factors such as lack of prior knowledge, poor understanding of fundamental concepts, or inadequate study habits.

With reference to the **(Fig 5.14)** we can observe that the output accuracy rate of the tested data is showing a correct respective accuracy that is higher accuracy rate **(98.84)** in advance level question and it reduced slightly **(96.20)** to the moderate question and then slightly reduction **(95.93)** in lower level, from this we can conclude that the stimulation of brain during advance level is high.

The present study aimed to investigate the physiological and cognitive responses of chess players when playing against a computer versus in a real-life context. Specifically, the study examined changes in heart rate variability (HRV) and the electroencephalographic (EEG) power spectrum, as well as the accuracy rates of participants in different levels of chess difficulty.

Results showed that participants exhibited higher accuracy rates when confronted with advanced level questions compared to moderate and lower-level questions. This suggests that the cognitive stimulation experienced during advanced level gameplay is higher, as reflected by the participants' performance.

Furthermore, the study found that familiarization with simulated practice led to changes in HRV and EEG power spectrum, indicating physiological and cognitive adaptations in response to the type of chess gameplay.

These findings align with previous research cited in the study, supporting the notion that cognitive demands vary depending on the level of chess difficulty and the context in which the game is played.

CHAPTER 6

SUMMARY AND CONCLUSION

The observed accuracy rates across different levels of aptitude questions in the cognitive domain reflect the varying cognitive demands and levels of proficiency among test-takers. Understanding these trends through the lens of Bloom's Taxonomy provides valuable insights for educators, test developers, and policymakers to enhance teaching, assessment, and support strategies.

In summary, the high accuracy rate in advanced level questions, medium accuracy rate in moderate level questions, and low accuracy rate in lower-level questions of aptitude tests in the cognitive domain can be explained effectively using Bloom's Taxonomy, highlighting the progression from lower to higher-order thinking skills.

Bloom's Taxonomy provides educators, curriculum developers, and instructional designers with a framework for designing learning objectives, assessments, and activities that target specific levels of cognitive complexity. By scaffolding learning experiences to progress through the taxonomy, educators can facilitate deeper understanding, critical thinking, and creativity among learners. Additionally, understanding Bloom's Taxonomy can help learners become more aware of their own thinking processes and develop metacognitive skills for self-regulated learning. Overall, Bloom's Taxonomy remains a valuable tool for promoting meaningful learning experiences and fostering intellectual growth across various domains of knowledge.

Future applications for this BIOPAC gadget include a variety of hospitals, healthcare settings, educational institutions, and many other locations that demand accurate physiological tests. Overall, the future development of Biopac devices is likely to be driven by advances in technology, emerging research trends, and the evolving needs of the scientific community and industry. These potential directions reflect ongoing efforts to improve the capabilities, usability, and versatility of physiological monitoring systems for a wide range of applications.

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