

EMOTION DETECTION THROUGH EEG USING BIOPAC

Submitted in partial fulfillment of the requirements for the award of
Master of Technology degree in Medical Instrumentation

By

Sounder. SK (41440012)



**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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MAY – 2023



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BONAFIDE CERTIFICATE

This is to certify that this project report is the bonafide work of **Sounder. SK** (Reg. No. **41440012**), who carried out the project entitled "**Emotion detection through EEG using BIOPAC**" under my supervision from **November 2022 to April 2023**.

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DECLARATION

I, **Sunder. SK** (Reg. No. **41440012**) hereby declare that the project report entitled "**Emotion detection through EEG using BIOPAC**" done by me under the guidance of Dr. **P. GRACE KANMANI PRINCE**, M.E., Ph.D., Department of Biomedical Engineering is submitted in partial fulfillment of the requirements for the award of **Master of Technology** degree in **Medical Instrumentation**.

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ACKNOWLEDGEMENT

I am pleased to acknowledge my sincere thanks to the **Board of Management of SATHYABAMA** for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

I convey my thanks to Dr. **T. SUDHAKAR**, M.Sc., Ph.D., Head of the Department, and Department of Biomedical Engineering for providing me necessary support and details at the right time during the progressive reviews.

I would like to express my sincere and deep sense of gratitude to my Project Guide Dr. **P. GRACE KANMANI PRINCE**, M.E., Ph.D., for her valuable guidance, suggestions, and constant encouragement that paved way for the successful completion of my project work.

I wish to express my thanks to all **Teaching** and **Non-teaching staff** of the Department of Biomedical Engineering who were helpful in many ways for the completion of the project.

I want to extend my sincerest thanks to all my **Family members** and **Friends** for their encouragement and support during my project work.

ABSTRACT

Emotions cause physiological and physical changes that have an impact on our bodies, minds, and the environment. EEG represents emotions, which represent a person's inner feelings, as a direct brain response to a stimulus. EEG-based emotion recognition is frequently utilized in affect computing to enhance human-machine interaction. EEG approach has benefits such as being non-invasive, having good temporal resolution, being economical, and being simple to use. Employing an audio-visual induction-based acquisition methodology, the participant's EEG signals are recorded while they are experiencing the four emotions of disgust, happiness, surprise, and fear. To categorize the EEG data, various readings have been taken and frequency has been analyzed. Using feature extraction for each sample, the dataset is varied based on each different emotion.

KEYWORDS: Emotion detection, EEG, Human machine interaction (HCI), Dataset

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LIST OF ABBREVIATIONS

AAM	-	Active Appearance Model
AFERS	-	Automated Face Expression Recognition System
BCI	-	Brain Computer Interfaces
BSL	-	BIOPAC Student Lab
CNN	-	Central Neural Network
CPU	-	Central Processing Unit
CV	-	Computer Vision
DEAP	-	Database for Emotional Analysis using Physiological Signals
DNN	-	Deep Neural Network
DWT	-	Discrete Wavelet Transform
EEG	-	Electroencephalogram
FACS	-	Facial Action Coding System
FMRI	-	Functional Magnetic Resonance Imaging
GND	-	Ground
HMI	-	Human Machine Interaction
IAPS	-	International Affective Picture System
LBWT	-	Lifting Based Wavelet Transforms
MATLAB	-	Matrix Laboratory
MRMR	-	Maximum Relevance Minimum Redundancy
PC	-	Personal Computer
RAVESS	-	Ryerson Audio-Visual database of Emotional Speech and song

SVM	-	Support Vector Machine
TESS	-	Top End Sleepiness Scale
USB	-	Universal Serial Bus

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CHAPTER 1

INTRODUCTION

Brain computer interfaces (BCI) research is expanding in recent years. The signals coming from the brain are analysed and recorded. Both physical and physiological impulses are contained in it. The detection of emotions now relies on real-time signals. Text, speech, gestures, and facial expressions can all be used to identify emotions, but electroencephalography produces the best results since it captures actual experiences directly. EEG has a great temporal resolution and is non-invasive. Numerous neurons move concurrently during neural activity in the brain, producing the necessary amounts of electric potential for an EEG to record electrical data. The sampling length, overlapping rate of sampling, and the beginning length of signals that need to be deleted can be determined by taking into account the outcomes from various subjects. Facial Action Coding System (FACS) was developed through industrial investigation of the relationships between muscle loss and the resulting aberrations in facial appearance. This attempt outlines a real-time, automatic facial emotion recognition system that uses a camera or open cv and inputs static photos or looped videos. Scientists are using EEG signals in a variety of research projects, including detecting spatial attention, predicting imagined hand movements on a subject, detecting potential issues related to brain disorders, and deep learning approaches in brain activity analysis through frequency determined in Hz in decimal, for example 34.01204mHz . The technology could be utilized for other purposes outside human-computer interaction, such as stress levels and emotional states of patients receiving medical care. The Histogram of Oriented Gradient (Hog) approach was used by the US business company "Affectiva", an emotion recognition Software Development Kit to extract features from facial expressions, and a Support Vector Machine (SVM) classifier was trained on 10,000 photos.

EMOTION:

Complex psychological experiences have a profound impact on every area of our lives, including cognition, perception, and decision-making. Subjective sensations may reveal a person's internal emotional condition physiological

signals are examples of internal/inward expressions, and audio/visual signals are examples of external/outward expressions. With the advancement of technology relating to human cognition, the significance of emotions has also become apparent. Four emotions - happy, sad, fear, and disgust can be used. Positive and negative attributes are separated. Valance arousal model: Valance denotes extremes of positive and negative emotion, arousal denotes excitement or drowsiness, and dominance denotes the intensity of the feeling. Emotional detection requires both physiological signals from various body areas, which are captured as sensory input, and EEG signals from the brain.

ELECTROENCEPHALOGRAPHY:

The most accurate technique to measure neurons is via an electroencephalogram (EEG), which is one instrument that can measure neural activity directly. The voltage fluctuation produced by ionic current flow with synaptic connections of neurons is the EEG signal. EEG sensors are the most important part of an EEG system used to record electrical activity produced by the brain. The electrical data is recorded when the sensors (electrodes) are positioned at the scalp surface. Expressive movement responders potentially taint the neuronal pattern of EEG measurements. This interference may make one EEG data point's accuracy less reliable. The bio-signals will subsequently be sent to the PC via an EEG device for recording. After then, a different PC is used to provide audio and visual stimuli to the subject to elicit the appropriate emotions. The five frequency bands of the brain that include useful information are delta (0–4Hz), theta (4–8Hz), alpha (8–13Hz), beta (13–30Hz), and gamma (30–70Hz). Deep sleep is when delta waves are detected.

BRAIN WAVES:

Our brain's neurons use electric impulse waves to communicate with one another. The brainwaves will be picked up by sensors by putting it on one's head. Functions are discovered using creating bandwidth divisions. The Discrete Wavelet Transform (DWT) is used to obtain 4 frequency bands, such as alpha, beta, delta, and theta. We need to pre-process signals, remove environment noise and drifts by using a 4-45Hz band pass filter while other sounds were classified as non-significant, before extracting features from EEG data and doing classification.

DELTA (δ) : Acts as cure and associated with sleep.

THETA (θ) : Involves in Deep relaxation, meditation, improved memory.

ALPHA (α) : Associated with Creativity, relaxation, visualization.

BETA (β) : Keeps mind focused, beware and involves in concentration.

GAMMA (γ) : Processing of language, memory, and regional learning.

These are the capabilities of EEG-derived brainwave signals.

1.1 OBJECTIVE OF THE PROJECT:

- Electroencephalography (EEG) systems from BIOPAC are designed to monitor, record, and examine electrical activity in the brain. These systems are made to give academics, medical professionals, and educators a way to monitor brain activity and comprehend how it connects to mental and behavioral functions. Some specific objectives are, identifying the brain activity patterns connected to various mental states, such as emotion, arousal, and attention. It helps to monitor and diagnose neurological conditions like dementia, epilepsy and traumatic brain injury. It also helps in recognizing how drug, alcohol and other chemicals affect brain.
- In EEG research, BIOPAC, a popular physiological data collecting and processing system, has been employed. The method of measuring the electrical activity of the brain is called electroencephalography, or EEG. In order to better understand brain function and behaviour, researchers can use BIOPAC to capture and analyse EEG data in real-time.
- Electrodes, amplifiers, and software for signal processing and analysis are some of the common components found in BIOPAC EEG systems. The scalp is covered with electrodes that are attached to an amplifier, which enhances the electrical signals coming from the brain. After being boosted, the signals are transferred into the BIOPAC data acquisition system, where they are collected and converted to digital form for analysis.
- Synchronizing EEG signals with other physiological measurements with BIOPAC is one of the main benefits of using it for EEG research. For instance, researchers can utilize BIOPAC to simultaneously record EEG data and

assess skin conductance, heart rate, and respiration. This gives them the opportunity to investigate the connection between brain activity and other physiological functions and to comprehend the mechanisms underlying different neurological and mental illnesses.

- BIOPAC also provides a vast array of tools for data processing and visualization. With the aid of these tools, researchers can study EEG data in a number of different ways, for as by producing time-frequency plots or topographic maps of brain activity. As a result, they are better able to comprehend the patterns of brain activity that support various cognitive and behavioural activities.
- All things considered, BIOPAC is an effective instrument for EEG research, enabling researchers to record, process, and analyze EEG signals in real-time, as well as to combine these signals with other physiological measurements. BIOPAC has grown to be a vital resource for scientists researching brain activity and behaviour because to its extensive set of tools and capabilities.

1.2 PLAN OF IMPLEMENTATION:

The project is implemented in various stages:

Stage 1: Placing electrodes on the specific sample or individual based on positive, negative, and grounding positions

Stage 2: Calibration and recording of brain signals are carried out

Stage 3: Video recordings with diverse emotional content are played to collect brain responses

Stage 4: Frequency of the brain signals are determined by the waterfall plot

Stage 5: In final stage, gathered data are represented.

STAGE 1:

On the basis of their brain signals, several people are enlisted to collect data based on different age category. According to the positive, negative, and grounding placements, electrodes are positioned on the underside of the earlobe.

STAGE 2:

The calibration for a demo sample comes before the real recording process

commences. Based on the test subject's eye movements and sample brain impulses, four channels of readings are produced.

STAGE 3:

Individuals are exposed to a variety of media contents that elicit distinct emotions. Hence, different parameters and frequencies can be used to record brain signals.

STAGE 4:

According to the emotions, each signal is captured consecutively in each segment. The waterfall plot is used in the research to help determine the frequency of the brain signals. Both the overall frequency and the signal frequency can be calculated separately.

STAGE 5:

The data from the collected brain samples are recorded and displayed in Excel sheets for easier comparison and subsequent research. The data are analyzed through google colaboratory.

1.3 ADVANTAGES OF THIS WORK:

The following list of advantages are

- The non-invasive BIOPAC EEG method does not require any invasive procedures or methods to gather data on brain activity.
- It enables researchers to study how the brain reacts to diverse stimuli and events since it can record changes in brain activity in real-time through its high temporal resolution.
- It is a safe procedure because it doesn't use radiation or have any negative side effects.
- This EEG reading is a less expensive option to other brain imaging procedures like functional magnetic resonance imaging (fMRI), which can be costly and need specialist facilities and equipment.
- Easy to use and can be set up quickly.

CHAPTER 2

LITERATURE SURVEY

Animesh Nema et al (2019) developed a system that allows us to take user speech as input and use the appropriate machine-learning algorithms to identify the mood. The speech will be recorded, and a mic will be used to track various emotional cues. Both males and females can recognize these moods, and the detection accuracy rises as the training set expands. The model is specifically designed to distinguish between male and female sounds, and it does so with 100% accuracy. With more than 70% accuracy, the model was trained to recognise emotions. More sample data can be used to prepare with greater precision.

Mansee Dhamal et al (2021) created an automatic system that can identify six emotions, as well as positive and negative percentages and graphs. So far, they have identified six emotions: anger, disgust, fear, happiness, sadness, and surprise. Additionally, positive, negative, and neutral feelings were assigned to the calculated emotion recognition scores. Then, they develop an app that rates each of the user's six emotions and displays both positive and bad feelings.

Jingxin Liu et al (2016) In the freely accessible dataset DEAP, this link is modelled using machine learning-based techniques (Database for Emotional Analysis using Physiological Signals). Raw EEG recordings are used to extract different aspects. Then, for feature selection, Maximum Relevance Minimum Redundancy (mRMR) was employed. These characteristics are used as input for machine learning techniques to create prediction models that pull emotional data from EEG signals. Based on this dataset, the models are assessed, and positive outcomes are obtained.

Wan Ismail (2016) had done the research. The focus of this research is on relationship-related and emotional EEG signals. The development of "mind-implementation of Robots" is the main goal of this recognition. The four components of the research methodology are as follows: I the respondent's visibility and EEG data were collected simultaneously; (ii) the process of complete data recording involved the capture of images using the camera and EEG; (iii) pre-processing, classification, and feature extraction was carried out simultaneously;

and (iv) the features extracted were classified to emotional faces using artificial intelligence techniques. As a result, this study is very helpful for police agencies conducting criminal investigations as well as doctors working in hospitals. This study also aids in the creation of a software package.

Namrata D Rupani et al (2020) conducted an observational study. The emphasis is on identifying emotions through additional analysis of EEG signals and other physiological signs. The study reviews various machine learning methods that have been applied to pre-process and categorize EEG data. Major components of the emotion identification process are analysed, including feature extraction, classification, and method comparison. To categorize the EEG data, various supervised machine-learning methods have been used. This research focuses on an exhaustive analysis of current systems and, based on the findings, suggests strategies that, when used, would produce high-quality outcomes. Emotion Detection Analysis using EEG and Physiological Signals for Hybrid Systems.

Manoharan L et al (2020) The goal of the project is to create a robot that will help disabled people live more independently by assisting them in their daily activities. The 63 biosensors are employed to record the EEG signal for a range of emotional states. After pre-processing the signals, two distinct Lifting Based Wavelet Transforms (LBWT) are used to extract three statistical features for the classification of human emotions. Results support the feasibility of evaluating human emotions from EEG signals using two alternative lifting scheme-based wavelet transforms.

Nandini K et al (2020) review techniques for emotion recognition with EEG reported in the last ten years. Our analysis of the EEG is primarily concerned with feature extraction, selection, and classification for emotion recognition. For researchers working to further the field of emotion identification using EEG, this survey will serve as a significant milestone.

Minakshi S. Panchal (2020) in this system used an online available DEAP database is used emotion detection in four classes (Happy, Angry, Sad, and Relaxed). Pre-processed EEG data can be found in the DEAP database. Discrete wavelet transforms are used to extract features in the four frequency bands delta, alpha, beta, and theta. Emotions are identified by comparing valence and arousal values. Class 1 is represented by the happy emotion, Class 2 by the furious

emotion, Class 3 by the sad emotion, and Class 4 by the relaxed emotion. Class1 has an accuracy rate of 73%, Class2 of 83%, Class3 of 77%, and Class4 of 75%.

Prof. V.D. Bharate et al (2017) The method locates the lip region, trims it for further categorization, and then extracts the features into vectorized form. Using Logistic Regression, extracted features are compared to a trained database. To get over the limitations of a personal computer and for higher image quality, an 8MP USB camera is employed. The essential hardware for this project is a Raspberry Pi running a Linux-based operating system.

Chalciya Elizabeth Rani P (2021) et al. In this system they used Standard Data FER2013, which has 30,219 photos total and an additional 24,282 and 5937 images used for training and validation, respectively. This project assists in identifying faces within a 48*48 pixels range and identifying the emotions present in the provided photographs. Humans can experience the basic five emotions happiness, sad, anger, neutrality, and surprise.

Raghav Puri (2018) et al, Archit Gupta (2018) et al. The user's emotion will be recognized in this work based on their facial expressions. These expressions can be formed from any previously stored image or the live feed provided by the system's camera. Human emotions may be recognized, and the computer vision business has a large field of study on which numerous studies have previously been conducted. Python, the Open Source Computer Vision Library (OpenCV), and NumPy were used to carry out the task. Emotion is predicted by comparing the scanned image (testing dataset) to the training dataset.

Shivam Malik (2020) et al, offers a deep neural network-based classification model of the emotions produced by talks (CNNs). We concentrated on the audio recordings found in the RAVESS (Ryerson Audio-Visual Database of Emotional Speech and Song) collection for this purpose. The TESS dataset, which includes a collection of 200 phrases said by two actresses in seven different emotions, is used for additional training and testing. Eight distinct emotions have been classified by the model.

Ahmet Ergun Gümüş (2022) et al. In this work, the EMOTIV EPOC EEG recognition system was utilized to elicit fear and neutral stimuli utilizing the International Affective Picture System (IAPS). EEG data were captured during the tests using the Test bench application. The IAPS images were projected on the screen in order to synchronize the EEG records. Following analysis, distinct time-

spectral signal activity patterns were seen in the left parietal lobe at the beta band and the right frontal lobe (F4) at the alpha band, respectively.

Abhirami (2020) et al. In this project, we're using MATLAB to analyse the human speech signal to identify various emotions, such as happiness, sadness, and anger. We will implement the Deep Neural Network (DNN) and Support Vector Machine (SVM) algorithms for emotion recognition and evaluate their effectiveness.

Vijayanand. G (2020) et al. An Automated Face Expression Recognition System (AFERS) has been suggested in this study. Three steps make up the suggested methodology: face detection, feature extraction, and facial expression recognition. Using the AAM (Active Appearance Model) approach, the first phase's output is 9 utilized to extract face features such the mouth, nose, and eyes. Automatic facial expression recognition is the third stage, and it is straightforward.

CHAPTER 3

AIM AND SCOPE

3.1 AIM:

In order to research brain activity and function, high-quality electroencephalography (EEG) data are being gathered from individuals while they are engaged in a variety of tasks or situations utilising the BIOPAC EEG system. Getting precise and accurate readings of the electrical activity in the brain is part of this. The end goal is to analyse the data and make significant deductions about the cognitive and physiological mechanisms that underlie behavioural patterns in humans.

3.1.1 BLOCK DIAGRAM:

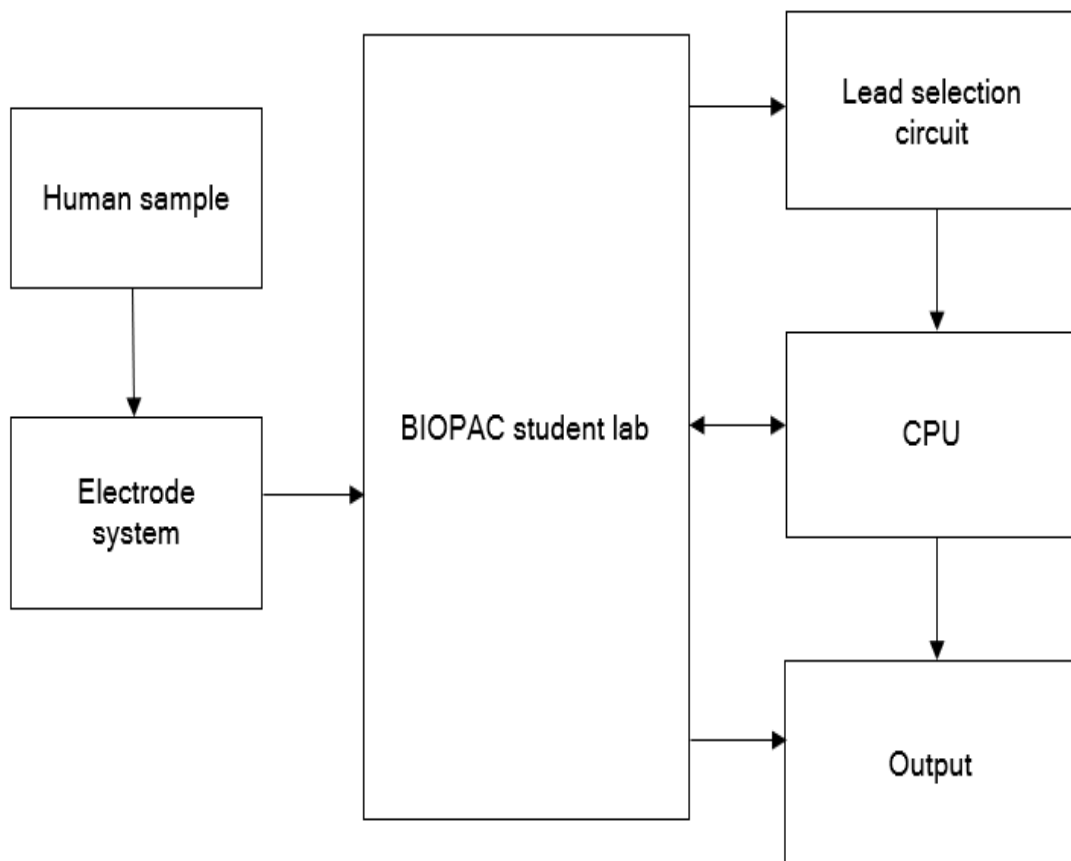


Fig. 3.1: Block diagram

3.2 SCOPE

Research: Biopac EEG equipment can be used in a variety of research fields, including neuroscience, psychology, and cognitive science. Researchers can utilize Biopac EEG to detect brain activity and analyze data in order to better understand cognitive functions such as attention, memory, and perception.

Clinical: Biopac EEG technology is used in clinical settings to diagnose and monitor illnesses like epilepsy, sleep problems, and brain traumas. EEG can assist clinicians in identifying aberrant brain activity and monitoring treatment efficacy.

Education: Biopac EEG equipment can also be used to teach pupils about the brain and its functions in educational settings. Students can learn how to collect and analyze EEG data, which can then be used to better understand various cognitive processes.

3.3 EXISTING SYSTEM:

DEAP (Database for Emotion Analysis using Physiological signals). This system offers a library of physiological signals, including EEG signals and others, that can be used to identify emotions. Additionally, it offers feature extraction and signal analysis software tools.

Emotive: A headset with EEG sensors and software for data processing and emotion recognition are part of this commercial system. Basic emotions like elation, contemplation, and frustration are all detectable by it.

EmoReact: This device analyses EEG waves and recognizes emotions using machine learning methods. It is capable of identifying five different emotions, such as joy, rage, and melancholy.

Brain Computer Interface: EEG signals are used by BCI systems to operate equipment like wheelchairs and prosthetic limbs. Due to research linking various EEG signal patterns to particular emotions, these devices can also be used to identify emotions.

AffectNet: Deep learning methods are used by this system to analyze EEG waves and identify emotions. Six various emotions, such as happiness, sadness, and rage, are detectable by it.

3.3.1 DISADVANTAGES:

SHORT COMINGS OF EXISTING SYSTEM:

There are certain limitations and potential shortcomings with using BIOPAC in clinical and research settings that should be understood.

COMPATIBILITY: Since BIOPAC hardware and software are often the only ones compatible with BIOPAC systems, researchers who want to use equipment from other manufacturers or combine BIOPAC data with data from other sources may have fewer possibilities.

LIMITED SAMPLES: The accuracy of data gathering for some applications may be impacted by the limitation on the sample rate of BIOPAC systems.

EXPENSIVE: Some researchers and institutions may find it difficult to use BIOPAC devices because of their high cost.

LIMITED PORTABILITY: BIOPAC systems are typically not very portable, making data collection difficult in certain settings or from certain populations.

3.4 PROPOSED SYSTEM:

The proposed method deals with the acquisition of data from diverse individuals using various video recordings that activate brain signals. The videos are shown to the samples to elicit their emotions and brain signal frequencies.

The BIOPAC aids in the determination of frequency and emotional variations by recording brain signal values based on EEG. This system increases data acquisition quality and reduces problems. Unlike MRI scans, this is more reliable, non-invasive, and risk-free.

CHAPTER 4

MATERIALS AND METHOD

4.1 SOFTWARE USED:

4.1.1 BIOPAC:

Students can record data from their own bodies, animals, or tissue preparations using the integrated BIOPAC Student Lab (BSL) Basic system. It provides a whole package of hardware, software, and educational materials for life science applications in higher education, such as ECG, EEG, EMG, and EOG. In order to boost interest and retention, the BSL System uses dynamic lessons with students as the subjects. Students are able to compare data from various experimental circumstances with peers in their group as well as with all other students in the lab. The system can be ordered a la carte or upgraded to create Advanced or Ultimate systems. Students are guided through the lectures by the BIOPAC Student Lab software using full-color onscreen instructions, a thorough lab manual, embedded procedure videos, and data samples. Results and measurements can be gathered into data reports that are part of the rich-text journals and sent to instructors via email or saving. BSL 3.7 is needed for MP30 or translations, and BSL 4 is available in English with compatibility for MP36, MP35, and MP45 hardware as shown in fig. 4.1 for Windows or Mac. Students can prepare for class, analyze data, share it, and submit it using Free Student Download. Software, a teacher's manual, and a data capture unit make up the BIOPAC Student Lab system. The program shows the numbers as waveforms on the monitor while the data acquisition equipment transforms incoming signals into digital signals that can be analyzed by a computer. The data collecting device uses USB to connect to a computer running Windows or Mac OS X.



Fig. 4.1: BIOPAC

Students have the option to record information about their heartbeat, brain waves, muscle activity, eye movement, and more. Students can learn physiology and the idea of electricity flowing through a living organism thanks to the system.

LEAD SELECTION CIRCUIT: A cable that connects electrodes to the BIOPAC device is the lead selection circuit. The device offers channel 1 and channel 2 as its two connectors. The port is known by the moniker SS2L as shown in fig 4.2. A completely isolated cable called the lead selection circuit allows for the connection and recording of physiological data.

The electrode is appropriately placed on the backside of the sample's earlobe.

A lead selection circuit is generally used by Biopac EEG systems to select and enhance the signals from particular scalp electrodes. The user can decide which electrodes are active and which ones are not by using the lead selection circuit, an electronic circuit.

In Biopac EEG systems, the lead selection circuit typically comprises of a number of switches or relays that the user can operate via software. The non-selected electrodes are unplugged while the selected electrodes are connected to the amplifier circuit's input by means of these switches or relays.

Additionally, filters that cut out undesired signals like interference and noise are part of the lead selection circuit.

Only the desired frequency range of the EEG signals is intended to pass through these filters and reach the amplifier circuit.

Overall, the lead selection circuit is an essential component of the Biopac EEG system because it enables the user to choose particular electrodes and filter out undesirable signals, which enhances the precision and quality of the EEG data that is captured.

The specifications of the lead selection circuit in a Biopac EEG system may vary depending on the specific model and version of the system. However, here are some general specifications that are common in Biopac EEG systems:

- Number of channels: Biopac EEG systems typically have multiple channels, ranging from 8 to 64 channels or more. The lead selection circuit allows the user to select which channels are active and which ones are not.
- Input impedance: The input impedance of the lead selection circuit is typically high, typically in the range of 100 Megaohms to 10 Gigaohms. This high impedance helps to minimize the loading effect on the electrodes and preserve the signal quality.
- Common mode rejection ratio (CMRR): The CMRR of the lead selection circuit is typically high, ranging from 80 to 120 dB or more. This high CMRR helps to reject common-mode signals such as power line interference and other sources of noise.
- Bandwidth: The bandwidth of the lead selection circuit is typically wide enough to accommodate the frequency range of the EEG signals, which is typically between 0.1 Hz to 100 Hz or more. The lead selection circuit may include high-pass and low-pass filters to remove unwanted signals outside this frequency range.
- Switching speed: The switching speed of the lead selection circuit should be fast enough to allow the user to switch between channels quickly and without introducing any latency in the signal.

These are some general specifications of the lead selection circuit in a Biopac EEG system. However, the actual specifications may vary depending on the specific model and version of the system.



Fig. 4.2: Lead selection circuit

SURFACE ELECTRODES: These electrodes are also known as disposable medical electrodes or adhesive electrodes. A disc constructed of a semi-rigid plastic composition with a recessed embossment in the centre as shown in fig 4.3. A metallic electrical contact is located in the centre of the embossed disc, with parts on either side.

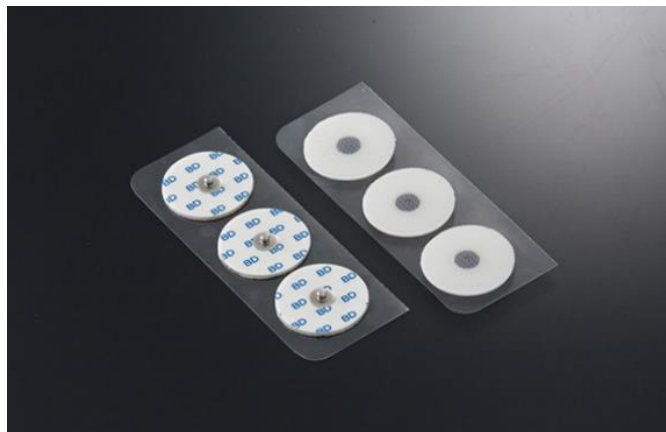


Fig. 4.3: Disposable surface electrodes

4.1.2 BSL SOFTWARE:

Onscreen lesson plans with improved student materials, such as sample data files and films, are included in the BSL 4 software as shown in fig. 4.4. The powerful and distinctive BIOPAC Student Lab System comes with comprehensive instructions on how to use it for data collection and analysis. EEG1 from L03 is the

lesson that was utilized to determine relaxation and brain rhythms. Software for signal processing and analysis is frequently included in BIOPAC EEG devices. With the help of this programme, it is possible to filter the EEG signals, eliminate noise and artefacts, and extract relevant data about brain activity, such as the frequency of various brain wave patterns. The research of brain activity and behaviour as well as the creation of fresh therapeutic approaches for neurological and psychiatric illnesses can both benefit from this knowledge.



Fig. 4.4: BSL software

1. Acqknowledge: This is the main software platform used by BIOPAC to gather, analyse, and show data. For gathering, examining, and visualizing physiological data, such as ECG, EEG, EMG, respiration, and more, AcqKnowledge offers a complete range of tools.
2. BIOPAC student lab: As I previously said, BIOPAC Student Lab is a software platform created especially for students to learn and carry out experiments using BIOPAC's selection of data gathering hardware.

Features of BIOPAC student lab:

1. Real-time data collection: Using a variety of physiological signals, the software enables students to gather data in real-time.

2. Data analysis instruments: Signal processing, filtering, and statistical analysis are just a few of the analysis tools available in the BIOPAC Student Lab to assist students in processing and analysing their data.
3. Experiment templates: Students can immediately get started using the pre-built experiment templates provided by the software.
4. Other software in the integration: MATLAB, LabVIEW, and Microsoft Excel are just a few of the programs that BIOPAC Student Lab may link with to offer further processing and analysis options.

4.2 HARDWARE USED:

4.2.1 SURFACE ELECTRODE GEL:

Surface electrodes are a class of electrodes that are placed on the skin of the subject. The techniques of electrocardiography, electromyography, and electroencephalography, which are used to record and assess the electrical activities of the heart, skeletal muscles, and neurons in the brain from the surface of the skin, respectively, have many important uses.

- Decreased contact impedance is one of the most significant objectives for suitable surface electrodes since it is necessary to achieve a good signal-to-noise ratio.
- The most popular kind of electrodes are gel electrodes.
- They are a regular component of clinical EEG recordings and have long served as the industry standard in EEG research. Therefore, high-quality bio-potential recordings are possible because to the gel that sits in between the skin and the electrode.
- Measurements of skin conductance or transthoracic impedance are two examples of other types of electrodes that can be used to measure the conductance of body parts.
- Additionally, gel is used in alternative EEG systems as the process enhance skin-electrode contact and connectivity.

- Benefits of using gel electrodes High-density EEG recordings should be possible. Very good signal quality; less prone to mains interference and movement artefacts than dry and water electrodes; and very low signal noise.
- Long-term recordings that are stable.

Several important benefits come with using surface electrodes in EEG.

- Non-invasive: Surface electrodes are safe and simple to use because they don't need to be implanted under the scalp or undergo any other invasive procedures.
- Comfortable: Surface electrodes are easy to wear and don't hurt or bother patients, making EEG a reasonably painless technique for people of all ages.
- Flexible: Surface electrodes can be positioned in a variety of places on the scalp to capture electrical activity from different parts of the brain, enabling a thorough evaluation of brain function.
- EEG is a cost-effective tool for identifying and tracking neurological problems since surface electrodes are less expensive than other electrode types utilised in the procedure, such as invasive electrodes or intracranial electrodes.
- Surface electrodes offer a high temporal resolution, which enables them to detect rapid changes in the electrical activity of the brain with high accuracy and precision. This property makes surface electrodes an excellent instrument for researching dynamic brain processes.

Thus, surface electrodes used in EEG provide a high-temporal-resolution tool for evaluating brain function and detecting neurological illnesses that is secure, comfortable, adaptable, affordable, and cost-effective. The introduction of surface electrodes has completely changed the discipline of neuroscience and brought up new perspectives on how the brain's intricate mechanisms function.

4.2.2 DISADVANTAGES:

- Gel electrode drawbacks to lower impedance, the skin must be prepped by softly scratching it.
- A trained specialist is necessary
- Participants may find it uncomfortable because they need to clean their hair and itching their skin can be unpleasant.
- The preparation process can take a while, the head cap needs to be cleaned, and drying the cap takes time.

4.3 METHODOLOGY:

An established electrode placement system is used to implant electrodes on specified parts of the scalp during the collecting of EEG data. The electrical signals produced by the neurons are then amplified and digitalized by the amplifier or recording device that is linked to the electrodes. Typically, the recorded EEG data takes the form of a time-series of voltage readings, where each voltage measurement represents the activity of a particular electrode at a certain time. Depending on the research objective and the experimental design, the data can be gathered over a period of several minutes to many hours.

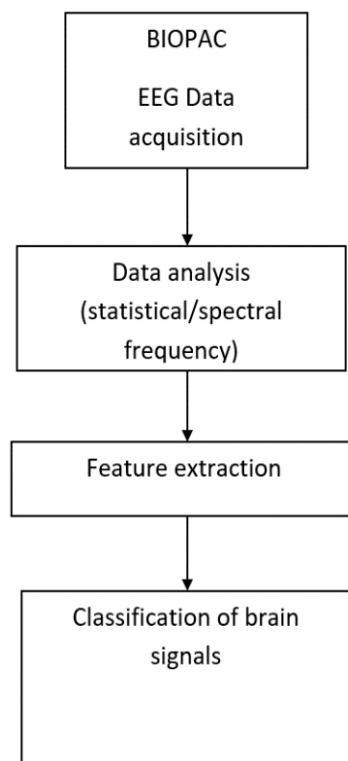


Fig. 4.5: Flow chart

Preparation: Electrodes are applied to the subject's scalp in order to get them ready for the EEG recording as shown in fig. 4.7. The usage of a particular EEG recording procedure will determine the number and placement of electrodes.



Fig. 4.6: All set BIOPAC kit

Connection: Utilizing insulated wires, the electrodes are connected to the BIOPAC EEG amplifier. A USB or Ethernet cable is often used to connect the amplifier to a computer or data collection device as shown in fig. 4.6.

Calibration: The EEG amplifier needs to be calibrated before recording in order to guarantee precise data. Applying a known voltage signal to the electrodes and tweaking the amplifier's parameters until the output corresponds to the anticipated values are required for this.



Fig. 4.7: Data acquisition process

Recording: The data recording can start as soon as the EEG amplifier is calibrated. It is possible to instruct the subject to carry out a certain task or just to unwind by closing their eyes. A period of time, often a few minutes to several hours, is used to constantly record the EEG signal. Before the real recording process starts, a demo sample is calibrated. Four channels of data are generated using the test subject's eye movements and a sample of their brain impulses. Individuals are exposed to a wide range of media contents with various emotional effects. This means that multiple parameters and frequencies can be employed to record brain signals as shown in fig. 4.8.



Fig. 4.8: BIOPAC EEG waveform

Data transfer: Following the completion of the recording, the data is moved from the BIOPAC program to a computer or data storage device for additional processing. Depending on the software being used, the data can be saved in many file formats, including .mat, .edf or.csv.

Interpretation: The outcomes of data analysis can also be evaluated to learn more about the brain mechanisms driving cognitive and behavioral activities. In order to spot variations or patterns, this may entail comparing the EEG signal across various experimental setups or subject groups. Each signal is recorded sequentially in each segment in accordance with the emotions. In order to estimate the frequency of the brain signals, the waterfall plot is utilized in the study. You can determine the signal frequency and the overall frequency individually. For simpler comparison and future research, the data from the acquired brain samples are stored and shown in Excel sheets. For analyzing those data, the excel sheets are saved in csv format and then fed to google colaboratory for feature extraction.

In order to investigate and comprehend brain activity as well as to identify and treat a variety of neurological illnesses, researchers and doctors use EEG data collecting as a key tool.

CHAPTER 5

RESULT AND DISCUSSION

5.1 INTRODUCTION:

The components are connected as illustrated in the block diagram, and data acquisition is completed. The BIOPAC then generates the matching waveform for the test sample. This waveform is then analyzed with BSL software, and the frequency of the brain signals is determined. The values are now gathered from the sample, and their emotion variability is categorized based on their ages.

5.2 PROCEDURE:

The required components are tested and calibrated. The subject is clearly explained concerning the method. The test sample is made to be at ease while the recording is taking place. The basic personal information of the subject is recorded. The subject is said to be still in order to avoid any form of artefacts that may occur throughout the recording technique. The person is also supposed to be calm and composed so that the EEG signals can be detected easily. The samples are exposed to the projected video recordings in order to elicit the appropriate emotional response.

DATA ACQUIRED:

A datasheet might contain emotional states including joy, sorrow, disgust, fear, and other pertinent emotions. Each emotional state's frequency would be calculated and represented as raw data as shown in fig.5.1. Along with any contextual details or other elements that might have influenced the emotional responses, the data may also include information on the strength or length of each emotional state.

A datasheet could include graphs or other visualizations in addition to the raw data to help show how the sample participants emotions were distributed.

In order to improve emotional intelligence, create more effective mental health interventions, or comprehend the emotional impact of specific events or stimuli, this could assist researchers or analysts in identifying patterns or trends in emotional responses.

Overall, a data sheet that includes the frequency of feelings like happiness, sadness, contempt, fear, and other pertinent feelings can offer insightful information about the emotional reactions of a group of people and be utilized for a number of research and analysis tasks.

S.No	SAMPLE	AGE	Frequency1-happy	Frequency2-sad	Frequency3-disgust	Frequency4-fear
1	Asphin	17	44.595088	71.607559	72.120409	79.20792
2	Nijo	17	42.653017	65.295461	67.114481	71.124694
3	Sunil kumar	18	57.126535	78.155529	88.160251	85.287846
4	Hanudeep	18	57.670126	69.129954	89.133422	81.333875
5	Premkumar	18	45.259108	67.681895	65.984823	95.328884
6	Ashith	19	55.417013	61.180789	91.167481	74.850299
7	Azar	19	48.911714	62.064102	59.95105	71.51005
8	Charan	19	56.19556	72.411296	68.291048	92.453008
9	Pravin	19	61.011832	66.914633	85.200922	80.33361
10	Abiraj	20	45.440486	63.343872	84.915416	84.402496
11	Arokiya	20	43.105764	68.00408	70.135239	77.530758
12	Jai	20	53.951982	74.156512	71.01246	87.32361
13	Jey surya	20	40.120361	65.550501	76.662115	71.393201
14	Raghul	20	38.84042	45.17732	65.17751	87.292239
15	Meenu	21	47.321813	67.294751	72.33273	78.400627
16	Sam	21	44.375416	62.87331	81.135902	94.339622
17	Saraswathi	21	46.915317	77.011936	75.901328	75.815011
18	Shanuja	21	53.177346	65.08298	98.866307	70.472163
19	Srinivasan	21	43.830813	85.506626	89.726334	94.250706
20	Ragul	21	30.390518	42.817383	62.806331	72.411296
21	Shyam	21	42.27436	74.654721	81.95281	85.178875
22	Indu	22	49.250661	78.647267	69.311904	77.451442
23	Jinu	22	44.883303	57.874564	72.61826	80.16032
24	Pavithra	22	40.941658	47.48338	70.005201	92.893635
25	Rozario	22	56.23366	72.506731	95.923261	90.124521
26	Vigneshwaran	23	58.771672	46.981442	70.237772	66.271654
27	Rahul	24	37.957866	79.459674	64.675691	90.497737
28	Adith	25	43.440486	63.343872	82.010307	84.402496
29	Sollen	25	31.550717	40.708343	62.670124	84.901292
30	Anand balaji	26	41.862047	74.878322	79.529144	93.529411

Fig. 5.1: Acquired sample data

The output is organized based on the age variance in the sample. Frequencies are used to determine the output. The objective of data collection is to analyze brain activity on various occasions and to find abnormalities in brain signals for future research purpose.

The first category includes people aged 17 to 20.

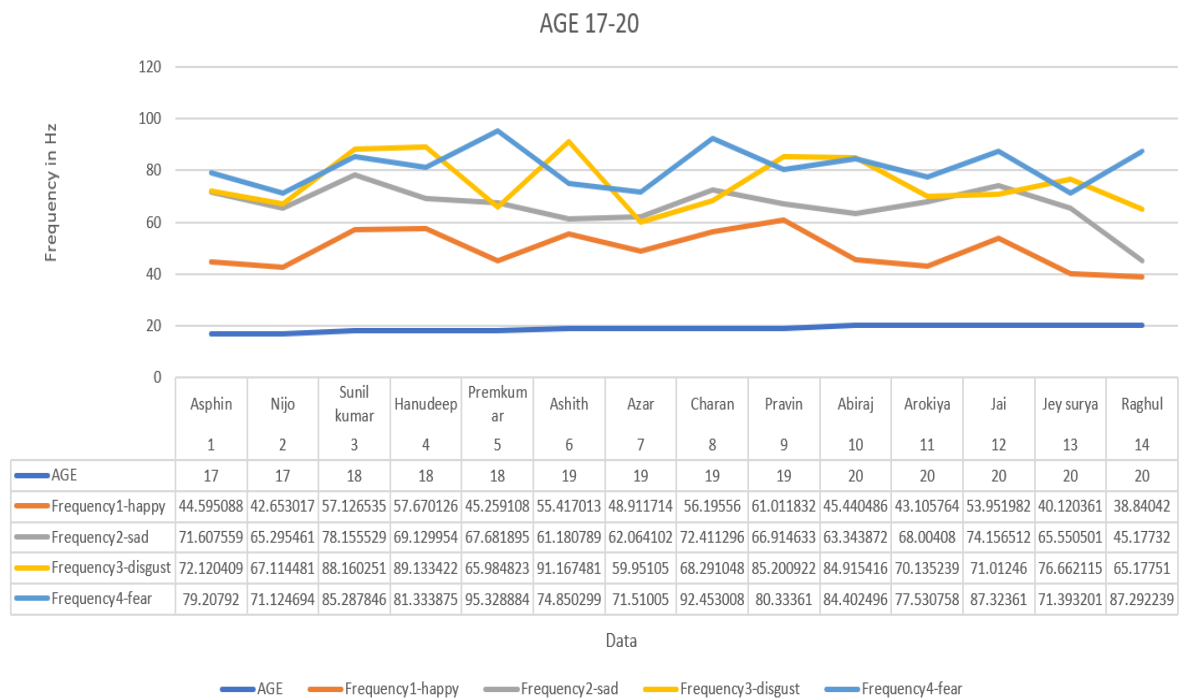


Fig. 5.2: Classification of first category

It could be helpful to visualize and analyze a group of people's emotional responses using a graph that shows emotional states as a function of frequency in Hz and age. The rate or strength of emotional reactions within the sample would be represented by the frequency in Hz on the graph y-axis as shown in fig.5.2.

On the graph, the x-axis would represent age of 17 to 20 denoted by various sections or bars. Additionally, each emotional state would be represented as a unique data series with a distinguishing color or symbol. In doing so, it would be simple to compare how people of different ages react emotionally.

The second category includes people aged 21-23.

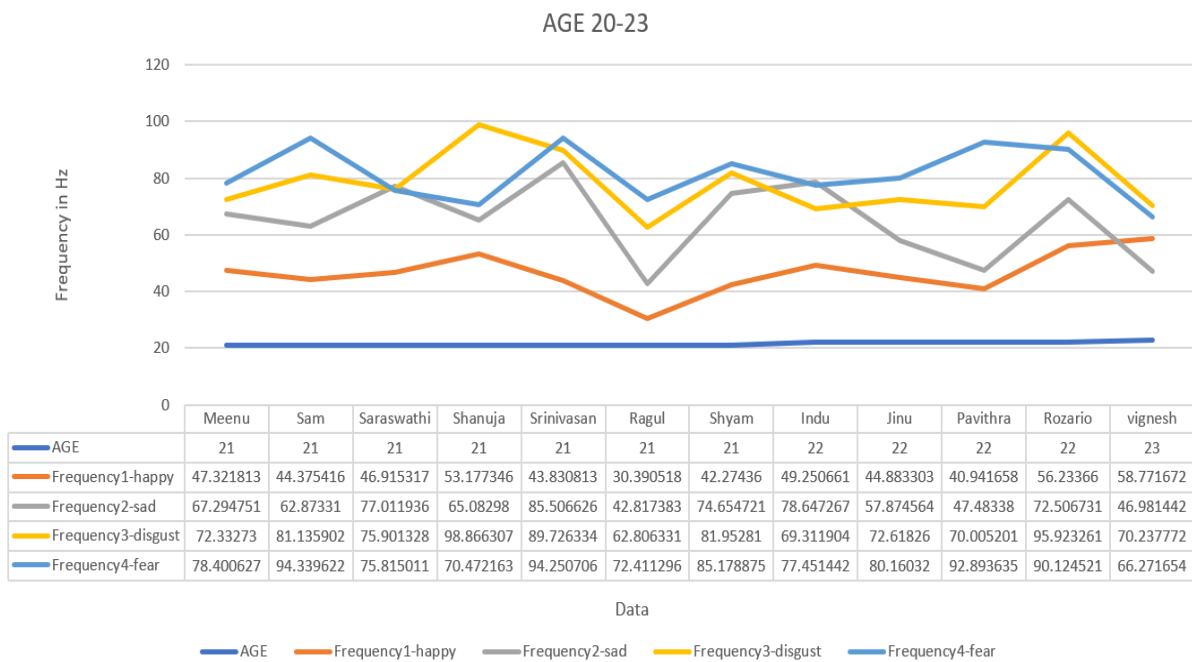


Fig. 5.3: Classification of second category

The frequency in Hz on the graph's y-axis, as illustrated in fig.5.3, would be used to represent the frequency or intensity of emotional reactions within the sample.

The age range of 21 to 23 would be represented by several sections or bars on the graph's x-axis. Each emotional state would also be depicted as a distinct data series with a recognizable color or symbol. This would make comparing the emotional responses of persons of various ages simple.

The third category includes people aged 24-26.

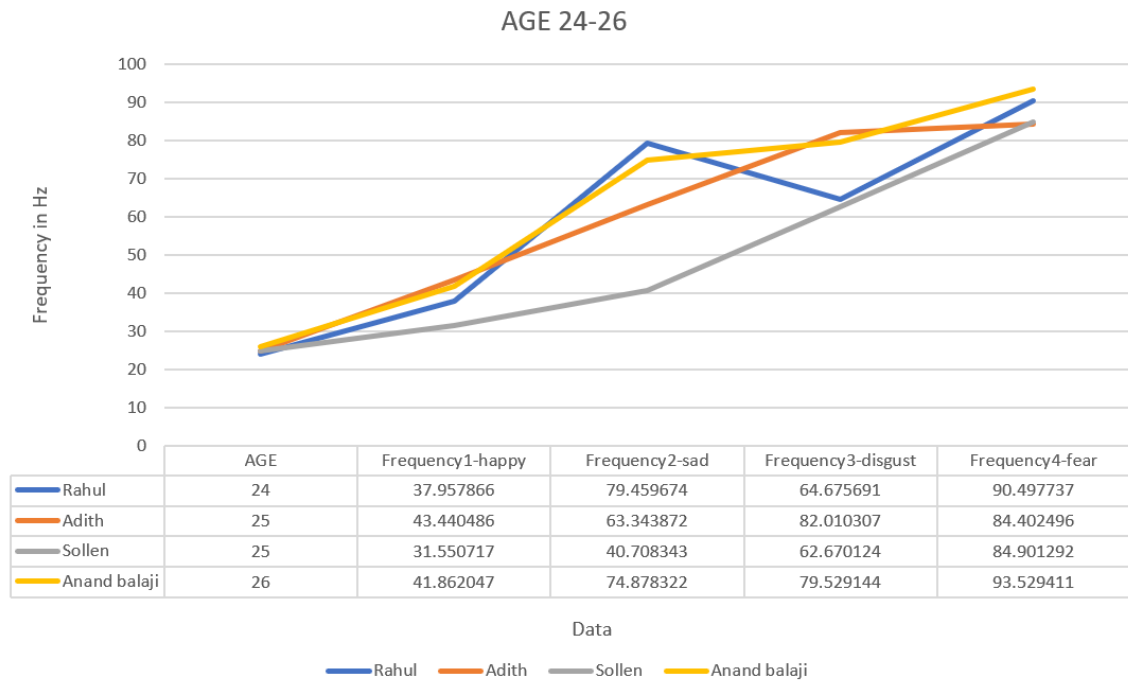


Fig. 5.4: Classification of third category

As seen in fig. 5.4, the frequency in Hz on the graph y-axis would be used to reflect the frequency or intensity of emotional reactions within the sample.

Multiple sections or bars on the graph x-axis would reflect the age range of 24 to 26. Furthermore, each emotional state would be represented as a unique data series with a distinctive hue or symbol. As a result, contrasting the emotional reactions of people of different ages would be simple.

The graph may also shed light on the connection between age and emotional expression or control. For instance, it might reveal whether certain emotional states change in frequency or intensity as people age and whether this changes between genders or age groups.

Overall, a visual representation of emotional states as a function of age, frequency in Hz, and gender could be a helpful tool for interpreting and examining emotional reactions within a sample. It could provide academics a better understanding of how emotional reactions vary across different age groups and emotional states and help them spot patterns or trends that might not be immediately obvious from raw data.

After saving the data in text/csv format as shown in fig. 5.5, the data are fed to google colaboratory program and then output is obtained in the form of graph.

1	frequency	average	out
2	42.653017	0.992574022	1
3	57.126535	0.998316072	1
4	57.670126	1.000020854	1
5	45.259108	0.999960031	1
6	55.417013	1.000151536	1
7	48.911714	1.003219133	1
8	56.19556	0.996571434	1
9	61.011832	0.996585949	1
10	45.440486	0.999688813	1
11	43.105764	0.989022819	1
12	53.951982	0.998627366	1
13	40.120361	1.000605941	1
14	38.84042	0.999450758	1
15	47.321813	0.998542124	1
16	44.375416	0.999492845	1
17	46.915317	0.999662724	1
18	53.177346	0.9986467	1
19	43.830813	0.999875753	1
20	30.390518	0.998569676	1
21	42.27436	0.998139038	1
22	49.250661	1.001700866	1
23	44.883303	1.000024409	1
24	40.941658	1.000536893	1
25	56.23366	0.947753871	1
26	58.771672	0.99864661	1
27	37.957866	1.001891696	1

Fig. 5.5: Frequency/Average in csv format

The data are then uploaded to a program for feature extraction. The data are analyzed and graphs are extracted as output as shown in fig. 5.6 for better study.

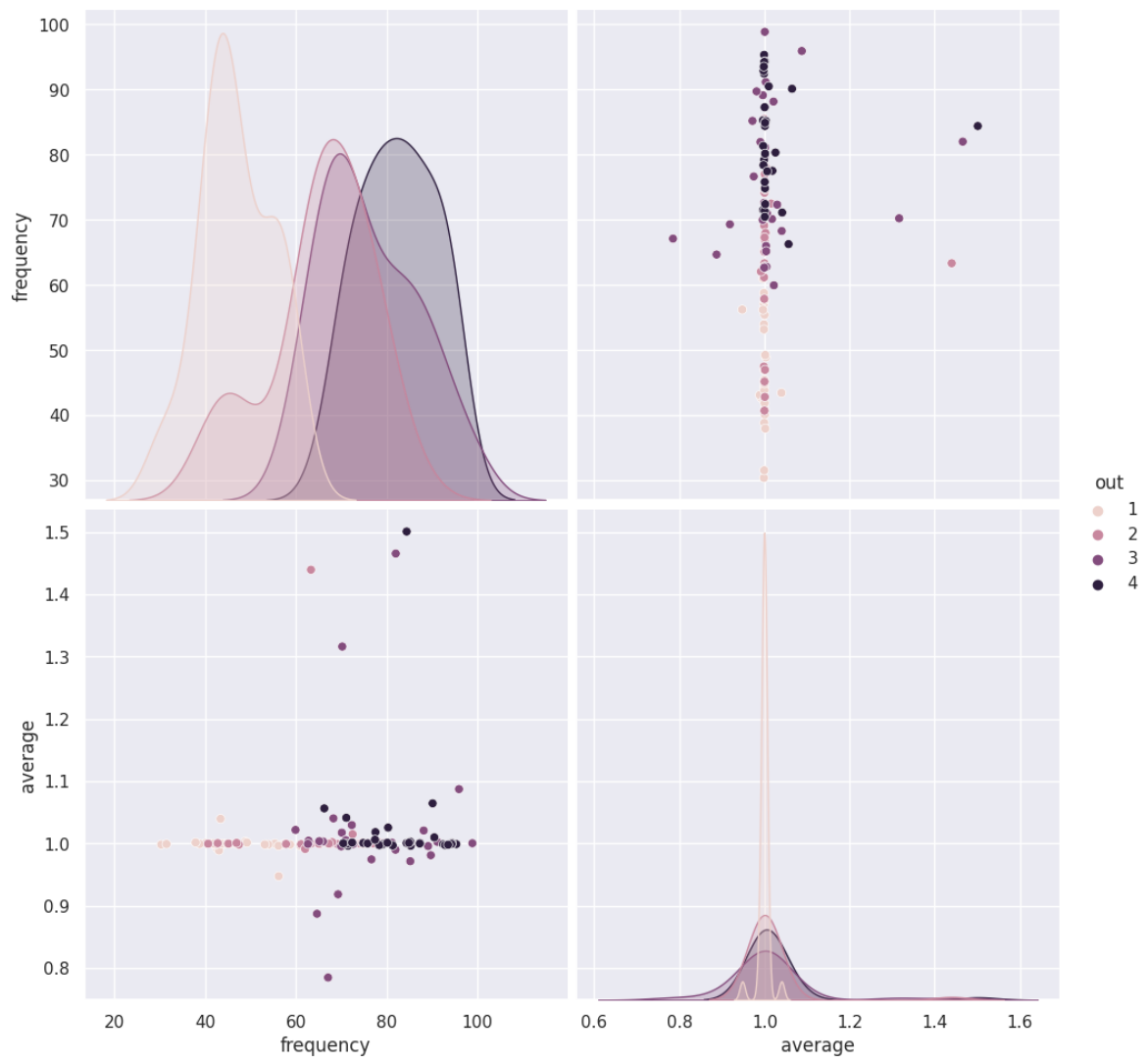


Fig. 5.6: Frequency/average graph

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

As a result, the BIOPAC EEG data gathering device is an effective instrument for non-invasively examining brain activity. Insights into the neurological correlates of many cognitive and physiological processes are valuable from the ability to precisely collect and analyze EEG data, which this technology enables. The system is appropriate for a variety of applications in neuroscience research, clinical diagnosis, and teaching because to its array of features and capabilities, including multi-channel recording, real-time signal processing, and adaptable analytic tools. Thus, the BIOPAC EEG data gathering system is a dependable and user-friendly tool for investigating brain activity, and it continues to be a crucial piece of technology for deepening our understanding of the brain.

Use of external software for filtering and refining the data acquired to remove artefacts and image processing is the work that will be done further.

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