International Journal for Multidisciplinary Research (IJFMR)

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

AI-Driven Integrated Hardware and Software Solution for EEG-Based Detection of Depression and Anxiety

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Abstract

Depression and anxiety are prevalent mental disorders that have impacted a substantial number of individuals worldwide, exceeding 300 million cases. The repercussions of the COVID-19 pandemic are expected to further escalate these figures due to the economic, social, and societal challenges faced by individuals. Extensive research has revealed distinctive asymmetry in frontal brain-wave activity among individuals with depression and anxiety compared to those without these disorders. Considering this, our research proposes a non-invasive method utilizing a wearable EEG device for the detection of depression and anxiety. The study encompasses essential components such as EEG device interfacing, data collection, preprocessing, feature extraction, data analysis, machine learning model training and evaluation, and the development of a mobile application enabling on-device inference and integration with a cloud database. EEG signals were collected from 30 individuals in a resting state using a single-electrode EEG sensor. Time and frequency domain analyses were conducted on the collected signals. Our machine learning model achieved a remarkable 93% accuracy in detecting depression and anxiety. Thus, the completed study comprises both hardware and software elements. The hardware component features the NeuroSky Mindwave wearable EEG sensor, while the software component includes machine learning models, an Android mobile application, and a data processing pipeline. This integrated system aims to provide a comprehensive solution for the detection and management of depression and anxiety, ultimately enhancing the well-being of individuals afflicted by these conditions.

Keywords: Electroencephalogram (EEG), NeuroSky, Mindwave, Depression

INTRODUCTION

Internet of Things (IoT) has become an essential part of different fields that provide smart services to end-users [1]. The concept of IoT aims at making the internet even more intriguing by enabling easy access and interaction with a wide variety of equipment. Although the uses of IoT in businesses, home automation, agriculture, transportation, and many more sectors are numerous but the impact of IoT on the healthcare system has been substantial due to its cutting-edge evolution [2]. The functionality of the IoT in the healthcare environment is further extended through mobile computing [2]. It assures advanced and reliable devices that can either be worn or embedded into the body to continuously monitor the health of patients [3]. The resulting data collected in this manner can be analyzed, processed, and mined to allow early detection of diseases [4]. The Internet of Things (IoT) has proven immensely advantageous in healthcare. Among various health conditions, depression is a significant contributor to the global disease burden. As per data from the World Health Organization, more than 300 million people worldwide of all age groups worldwide are estimated to be affected by depression [5]. Additionally, it is noteworthy that individuals diagnosed with depression often exhibit symptoms of anxiety disorders, while individuals experiencing anxiety are prone to developing depression. Distinguishing between these two conditions can be challenging; however, it is crucial to identify and address both mental illnesses [6]. Depression manifests through symptoms such as a persistently depressed mood, decreased energy levels, loss of interest, feelings of guilt or helplessness, disruptions in sleep or appetite, and difficulties in concentration. Conversely, anxiety, characterized by fear and excessive worry, can give rise to irrational thoughts and fears that interfere with daily life [7]. These mental disorders frequently originate at a young age, impair individuals' functioning, and often recur. Those suffering from neurological disorders face severe conditions and significant social pressures [8]. Existing methods for diagnosing depression predominantly depend on human expertise, thereby introducing subjectivity into the diagnostic process. Consequently, these limitations can substantially impair an individual's ability to fulfill daily responsibilities and hinder the receipt of appropriate treatment. In severe cases, depression can even culminate in suicide attempts [9].

According to an article published in the daily newspaper, the outbreak of coronavirus disease (COVID-19) has shaken the global economic, societal, and healthcare systems. People staying at home in self-isolation are under physical and emotional pressure [10]. Despite available treatments, a concerning trend persists where 40% of individuals grappling with depression or anxiety choose not to seek treatment. Furthermore, among those who do seek help, less than half receive the beneficial treatment they require. [11]. Given such circumstances, the objective approach is essential to address and treat such mental health illnesses. Around the world, there has been increasing emphasis on treatment and active illness management for people with neurological disorders, including depression and anxiety [12]. Some methods that are used to detect and record irregularities in daily living and measure the activity of electric brain pulse [13]. These methods include signal capturing through scalp electroencephalogram (EEG), electrocardiography, accelerometry, electrodermal activity, and video recording [14]. Accelerometer records the changes in the direction and velocity of the patients, which can help in the detection and recognition of different Activities of Daily Living (ADLs). EEG and electrocardiography are used for measuring the activity of electric brain pulses with the use of electrodes [14]. ECG is the recording of the electrocardiograph of the patients and the measuring of the heart rate (HR) which is an important parameter for the detection of anxiety among patients [15]. EEG is a wearable sensor that measures the electrical activity of brain cells. The acquisition of EEG through single an electrode has inherent shortcoming of low measurement confidence and more errors, but it provides a more wearable solution for continuous health monitoring. Hence, EEG can be used as a tool for making an objective diagnosis of depression [15]. This research paper introduces a non-invasive approach for monitoring depression by utilizing patient EEG signals. EEG signals, which capture brain neurons' spontaneous and rhythmic electrical activity, are recorded from the scalp's surface [16]. In this study, the EEG signals of the targeted population are collected during a resting state. The proposed method allows for the acquisition of EEG signals using various medical devices, enabling monitoring individuals' brain activity in their daily lives. Recently a wearable device used to gain the EEG signals is NeuroSky MindwaveMobile 2 ®.

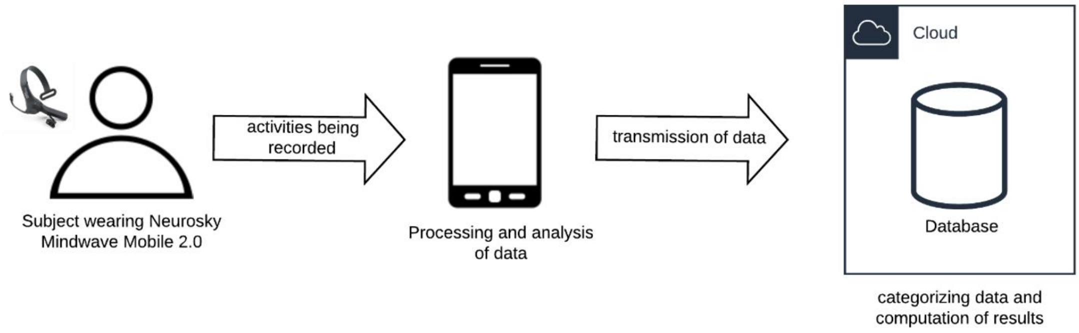

Fig 1. Proposed System Diagram

The primary objective of this research is to utilize wearable devices for detecting and recognizing depression. The data collection involves interfacing with the NeuroSky Mindwave device using the Neuro Experimenter app. Once the data is collected, preprocessing techniques are applied to enhance quality. Subsequently, the frequency components of the EEG signals are segmented into different wave bands [17]. Various Machine Learning algorithms will be employed to train data models to determine the most accurate algorithm for this task. Figure 2 illustrates a sample signal of EEG data obtained from a normal individual and a person with depression [18].

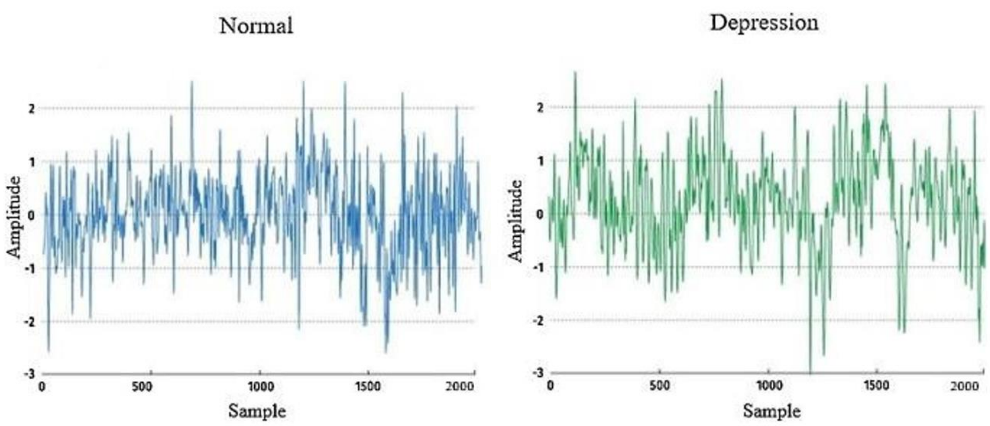

Fig 2. Proposed Sample Normal & Depressive EEG Signals [18]

Figure 2 depicts sample EEG signals obtained from the left and right hemispheres of a normal subject and an individual diagnosed with depression. These signals were acquired from the Psychiatry Department of the Medical College of Calicut. Acharya et al. [18] comprehensively review recent research on Computer-Aided Depression (CAD) using EEG signals. The CAD system described in the study can be utilized by specialists to validate their diagnosis or by non-specialists for preliminary diagnosis [18]. The study involves an in-depth analysis of EEG signals, focusing on the extraction of relative wavelet energy and a range of entropy features derived from the Discrete Wavelet Transform (DWT) coefficients. These extracted features serve as inputs for a meticulously designed two-layer feed-forward Artificial Neural Network (ANN) classifier. The primary objective of this research is to effectively discriminate EEG signals corresponding to individuals with normal mental states from those exhibiting symptoms of depression. Remarkably, this approach yields an impressive accuracy rate of 98.11%. It's important to emphasize that all aspects of this study are conducted with utmost rigor to ensure the highest standards of scientific integrity and validity [18]. The developed system will undergo testing on diverse individuals to validate its accuracy. Additionally, a comparative analysis will be conducted between the developed and existing accelerometry systems to ascertain the improved accuracy anticipated with EEG-based detection.

LITERATURE REVIEWS

The Internet of Things (IoT) is a way of connectivity for anything, at any time, and anywhere in the world. It has a great impact on our professional as well as personal lives [21]. We are entering the internet of things era, in which innovative types of communication take place between human beings and objects, and between objects themselves [22]. Over the past few years, social media networks have significantly grown in both scale and functionality. Platforms such as Facebook and Twitter have evolved into vast reservoirs of publicly accessible information. Across the world, millions of users engage in the exchange of information and sentiments daily. The Internet of Things (IoT) provides a distinctive opportunity to gather data and monitor the operational behavior of various products, services, and equipment in real-world settings. This data can enable devices or things to acquire intelligence by leveraging Machine Learning techniques. Machine Learning algorithms analyze and learn from the collected data, allowing devices to adapt, optimize, and make informed decisions based on the observed patterns and insights derived from the data. This integration of IoT and Machine Learning empowers devices and things to become intelligent and enhance their functionality dynamically and data driven. The IoT supports the idea of communication between humans & things, and between multiple things. With the help of IoT, it is possible to merge the physical and informational world into one. It uses sensors, which help in removing the gap between both worlds. The sensors collect the data and convert this data into useful information [23]. Healthcare is a very important part of today’s world, with new illnesses being discovered every few months. Technology cannot eradicate the growing illnesses, but it can provide greater accessibility and healthcare which is easy on pocket [24]. In today’s world, IoT has a great impact and extensive applicability in many fields and professions, including healthcare. The involvement of technology in healthcare methods, enhances operational efficiency of medical centers and patients get improved treatment. IoT provides unparalleled benefits in the field of healthcare. Some of them are stated below IoT can be beneficial to society in many ways [25]

IoT provides effective delivery service with its machine-to-machine communication, data movement, and information exchange. The modern connectivity protocols such as Bluetooth, Z-wave, Wi-Fi, etc. have changed the ways healthcare personnel spot ailments in patients. Consequently, these technology-driven methods, cut down the cost, unnecessary visits, improved planning, and better utilization of resources [26]. With cloud access, a large amount of data can be stored easily in very less time. But unavailability to the access of cloud makes it harder to manage and store the data and manually analyzing it is a tough bet. With the help of IoT devices, there is no need to store the raw data as it collects, reports, and analyses the real-time data. Moreover, organizations are given access to vital analytics of healthcare and data driven insights which is less prone to errors and speeds up the decision-making [26].

A neurological disorder is a medical condition that specifically impacts the functioning of the nervous system in the human body. It encompasses diseases that impact the central and peripheral nervous system, including the brain, spine, and connecting nerves. Neurological disorders can arise from various factors, such as biochemical, structural, or electrical abnormalities in the brain or nerves. These disorders manifest through a range of symptoms, including loss of sensation, changes in consciousness, pain, seizures, and muscle weakness. There are over 600 known neurological diseases, some common and recognized, while others rare. Neurological disorders include epilepsy, depression, anxiety, stroke, and brain tumors. Proper assessment and treatment of these disorders require the expertise of neurological specialists and clinical neuropsychologists [27]. Additionally, these disorders can impact a person's memory and mood. The causes of neurological disorders are multifaceted, including genetic factors, environmental influences, physical injuries, infections, and the affected individual's lifestyle. [28].

The overall burden of neurological diseases is around 6.5% in the whole world. The range in lower-income countries is around 4-5% whereas in high-income countries this range is 10-11% [30]. Deaths and disabilities are because of neurological diseases is even higher than heart diseases, AIDS, neoplasms, and Tuberculosis. The growing number of neurological diseases in developed countries is due to the urbanization of the population, increasing life expectancy, and better diagnostic facilities. According to a survey, everyone in six of the world population suffers from these disorders. According to a new United Nations report, about 6.8 million people are dying each year due to neurological disorders [31].

The combined average prevalence of Depression and Anxiety in both men and women, as reported in six studies conducted on random community samples, was 33.62%. One study focused on women aged 15-49, revealing a prevalence rate of 28.8%, while another study involving young men with an average age of 18 reported a prevalence rate of 33%. In 2017, the World Health Organization (WHO) released the latest statistics indicating that approximately 322 million people, equivalent to 4.4% of the global population, were affected by depression. [32]. Presently, insufficient data exists regarding the epidemiology of NDs in Pakistan. However, research conducted in Pakistan's third largest city of Pakistan Faisalabad (in the stretch of March 2015 to May 2015) suggests that due to prolonged life expectancy in developing countries like Pakistan there is a significant rise in the status of NDs. The research, conducted on 3000 patients, deduced that 19.6% of the total population is suffering from depression while 16.6% has epilepsy, and 15.2% has a migraine. Disc prolapsed population is 8.8%, people suffering from paralysis constitute 8.5% of the study subjects, trauma patients constitute 5.3% of the patients, while schizophrenia patients are 2.7%, 1.6% had tumor, 1.7% has dementia, mania 0.8%, acute psychological disorder 1.4%, disruptive behavior disorder 0.6%, bipolar affective disorder 0.7% [33]

Depression, a major depressive disorder, is projected to become the second most prevalent illness globally within the next decade. Approximately one in five women and one in twelve men are estimated to experience depression, characterized by a range of symptoms. such as persistent feelings of fatigue, hopelessness, worthlessness, restlessness, difficulty concentrating, indecisiveness, or recurrent thoughts of death for at least two weeks suggest the likelihood of depression. Physical manifestations of the condition may also occur, as the brain chemicals associated with depression play a significant role in mood and pain regulation. At its worst, depression can lead to suicidal ideation, with approximately 800,000 individuals worldwide losing their lives to suicide each year, ranking it the second leading cause of death [34]. Despite its high prevalence, individuals facing depression often encounter barriers such as social stigma, limited resources, and inadequate access to proper treatment for mental disorders. Additionally, incorrect assessment or diagnosis is a common challenge, with many patients being prescribed antidepressant medications without comprehensive evaluation [35]. The global burden of mental health conditions is steadily increasing.

Electroencephalogram (EEG) is a widely used method for recording brain wave activity in animals and humans. It is favored for its high resolution, safety, and ease of use. EEG signals play a crucial role in evaluating brain activity and emotional states. Research has shown that the parietal lobe EEG signals are associated with emotional states, cognitive tasks, and frequency domain features of EEG can predict levels of attention and vigilance [41][42]. Consequently, EEG signals are valuable in diagnosing brain disorders such as insomnia, epilepsy, anxiety, and depression. In recent years, EEG has gained significant attention due to its higher temporal resolution, simplicity, and lower maintenance costs [12]. The most common method for acquiring EEG signals is placing standard electrodes using the 10-20 system. However, EEG signals are non-stationary and have low spatial resolution, making them susceptible to artifacts caused by eye blinks, movements, muscle activity, heartbeats, and power line interferences [42]. The frequency components of EEG signals are typically divided into five wavebands [43].

- Delta waves, with a frequency range of 0.5Hz to 4Hz, are generated during the deepest state of meditation or dreamless sleep.
- Theta waves, ranging from 4Hz to 8Hz, are produced during sleep or deep meditation.
- Alpha waves, ranging from 8Hz to 12Hz, are typically dominant during periods of relaxed thoughts and certain states of meditation.
- Beta waves, falling within the range of 12Hz to 35Hz, are present in our typical wakeful condition and when we concentrate on activities.
- Gamma waves, with a frequency range of 35Hz and above, tend to dominate when there is simultaneous thought processing occurring in different areas of the brain.

Multiple EEG sensors are typically kept on a participant's head to capture brainwaves, enabling invasive brain activity detection. The pattern and intensity of these brainwaves provide insights into the type of activity an individual is engaged in. However, this process necessitates a controlled environment, restricting the subject's freedom of movement and preventing them from performing activities of daily living (ADLs) due to the cumbersome headgear and wires involved. In light of this, we aim to employ a single-channel EEG sensor capable of recording and reporting brainwaves specifically from the frontal part of the brain. This sensor must be wearable and non-invasive [44]. One such device that meets these requirements is the NeuroSky Mind Wave Mobile 2.0. This portable EEG sensor features a single electrode positioned above the left eyebrow of the user, with a reference point attached to the earlobe. The sensor measures the brain's electrical signals, and the collected data is transmitted to the user's laptop or mobile device via Bluetooth [45]. The data is captured as brainwaves, facilitating further analysis and interpretation.

Following the Signal Acquisition phase, the acquired brain signals require pre-processing due to contamination by noise and artifacts. Common artifacts in EEG signals include eye blinks, eye movements (EOG), and heartbeat (ECG). Techniques such as Common Average Referencing (CAR), Surface Laplacian (SL), Independent Component Analysis (ICA), and Common Spatial Patterns (CSP) can be employed to remove these artifacts. ICA, CAR, and adaptive filtering are commonly used among these techniques. EEG offers several advantages, including high temporal resolution, safety, and ease of use. However, there are also certain disadvantages associated with EEG signals. These include susceptibility to artifacts caused by EOG signals, ECG signals, muscular activities, and power line interference. These artifacts can affect the EEG data quality and must be appropriately addressed during pre-processing to ensure accurate analysis and interpretation of the signals. [46]

Machine Learning is a field that involves using algorithms and models to generate desired outputs based on given inputs through the process of learning from data. It has been widely and successfully applied to various signal-processing problems. One common type of Machine Learning is Supervised Learning, where the mapping from inputs to outputs is learned from labeled training data. Unsupervised Learning is primarily concerned with the exploration and acquisition of patterns within unlabeled data, such as the identification of clusters among similar customers. In contrast, Semi-Supervised Learning amalgamates both labeled and unlabeled datasets during the training phase. On the other hand, Reinforcement Learning revolves around the acquisition of skills for decision-making in various states, guided by observed rewards. [47].

Classification and Regression are prevalent forms of Machine Learning problems. Classification tasks aim to predict a label or class from a set of possible labels, such as determining whether an image depicts a cat or a dog. In Regression tasks, the objective is to estimate or predict a continuous numeric value as the output variable., like the price of a house, based on various features. Machine Learning input data exhibits variability based on the domain, encompassing diverse forms such as images in the realm of Computer Vision, textual content in the domain of Natural Language Processing, a mix of numeric and categorical attributes in the arena of tabular data analytics, and numerical signals in the context of Signal Processing and Time-Series Models. In the context of this study, EEG provides time-series signals, and the focus is primarily on utilizing supervised learning techniques to classify these time-series signal data. The Machine Learning models will be trained using labeled data representing different classes, such as depression or mental health disorders. The objective is to classify and predict the class label from a given input signal [47]. Some well-known Machine Learning algorithms include Support Vector Machines, Random Forest, Naive Bayes, Decision Trees, and K-Nearest Neighbor algorithms.

RESEARCG METHOLOGY

The goal of this research is to create an EEG and Machine Learning based system with the aim of estimating depression based on the EEG signals provided by users as input.

A. WORKING AND ARCHITECTURE OF THE DEVELOPED SYSTEM

The user uses the NeuroSky Mindwave Mobile EEG sensor for sampling EEG data of short time intervals through the Neuro Experimenter computer application, which performs signal pre-processing and frequency bands extraction.

- A CSV file containing processed frequency bands data is generated, which is transferred to the mobile app.
- A Machine Learning model was created using the Sklearn library, utilizing the EEG frequency bands data as the input attributes. Data analysis and evaluations of the model were conducted to assess its performance. The model was converted into a Java file using Sklearn Porter to run on Android mobile devices.
- The user enters information to login into the account on the mobile app.
- The file is loaded and parsed, and some pre-processing steps like standardization are performed on mobile to generate input for the model.
- The embedded Machine Learning model is used for on-device inference. The model classifies the EEG signal data into three classes namely minimal depression, moderate depression, and severe depression. The results are displayed through the app interface.
- The user data is uploaded to the Firebase cloud database through the mobile app for record and future usage.

The diagram presented below illustrates a visual depiction of the functioning of the comprehensive system for the Detection and Classification of Depression through EEG.

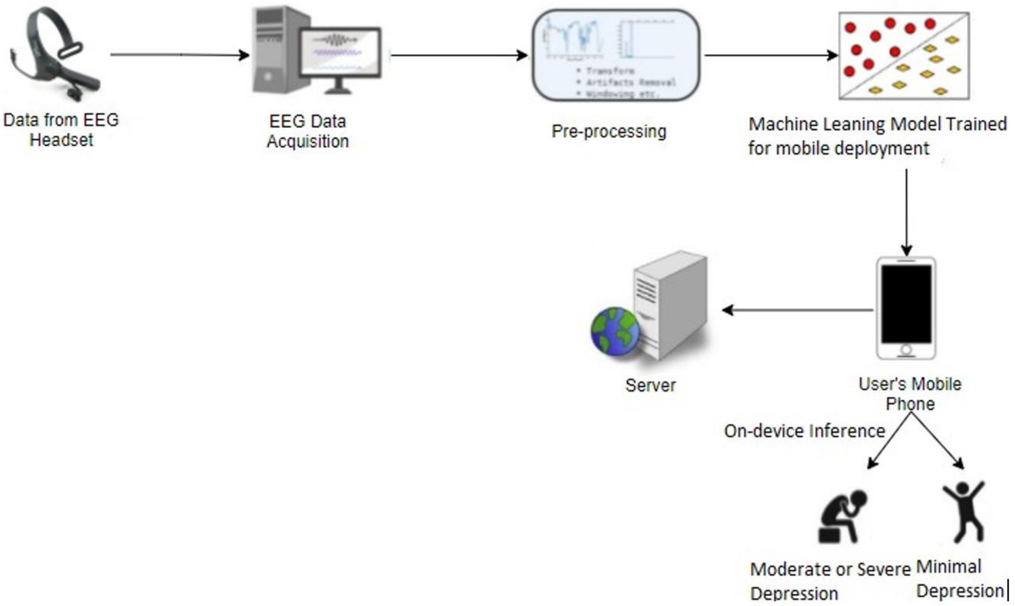

Fig 3. Overview of proposed work

B. MODULES FOR DESIGNING

The proposed work incorporated various modules to achieve its objectives. These modules were designed to address specific aspects of the study and contribute to the overall functionality. These include different hardware modules, software modules, and machine learning algorithms. The hardware modules, software modules and machine learning algorithms used for the design and implementation have been provided below.

a. Hardware Module

The hardware components used for the implementation of detection of depression are:

1. NeuroSky Mindwave mobile 2.0
2. Android Smartphone

1. NeuroSky Mindwave mobile 2.0

The NeuroSky MindWave Mobile 2, developed by NeuroSky, is an electronic circuit that incorporates dry electrodes. The device contains an EEG headset, an ear-clip, and a sensor arm. The ear clip houses the reference and ground electrodes, while the EEG electrode is positioned on the sensor arm, which sits on the forehead. The purpose of the device is to measure the brain generated electrical signals. The gathered data is then transmitted to the user's laptop or mobile device through Bluetooth connectivity. NeuroSky Mindwave Mobile 2.0 is used in the research as the portable EEG sensor to gather the EEG signals of the user. It collects the data in the form of brain waves, each having a different frequency, amplitude, and meaning. These brain waves are divided into five bands: delta wave.

2. Android Smartphone

A Smartphone is a cellular phone which consists of different types of built-in sensors and OS with support for advanced software and computing. The mobile app in this study is designed for smartphones with Android OS. The app is used for on-device ML model inference, results in display and uploading data to cloud database.

b. Software Module

The following software will be used for the designing and implementation of the proposed work:

1. MATLAB

MATLAB, an acronym for Matrix Laboratory, is an interactive system designed for technical computing. It is a programming environment where the fundamental data element is an array, and there is no need for explicit dimensioning of variables. This feature enables users to efficiently solve various technical computing problems, particularly those involving matrix and vector operations. MATLAB provides a comprehensive set of tools and functions that facilitate data analysis, algorithm development, modeling, simulation, and visualization. Its capabilities make it a powerful tool for researchers, engineers, and scientists in various domains. It helps in acquiring, measuring, transforming, filtering, and visualizing a signal. There are a lot of built-in functions available, making programming much easier for the user. The volunteer's daily life activity related signal (sitting, walking, focusing, etc.) is attained by electrodes of the headset. The collected EEG signal is wirelessly transmitted to the laptop using a Bluetooth dongle. The EEG dataset is recorded with a sampling frequency of 128Hz, capturing the brain's electrical activity at a rate of 128 samples per second. The recorded data is saved as edf (European data format) file. This format is commonly used for storing multichannel physiological data, including EEG signals, and allows for compatibility and easy analysis with various EEG data processing tools and software.

2. NeuroSky Mindwave Tutorial

NeuroSky Mindwave Tutorial is a tutorial application to help and guide the users in how to set up their NeuroSky Mindwave Mobile 2.0.The user has to first select the com port at which their headset is connected. Then the user selects their country, to set up the appropriate frequency. Once done, the step-by-step procedure is given. Moreover, the user can also test their meditation, blinking, and attention levels using this software. The purpose of using this software in our research is to easily check if the sensor fitting is properly done and for the basic understanding of NeuroSky Mindwave Mobile headset.

3. Think Gear- Application program interface

Think Gear is the technology within each NeuroSky device that enables a user to interact with the user's brain waves. NeuroSky Mobile enables the measurement, amplification, filtering, and analysis of EEG signals and brainwaves. To utilize its functionality, the NeuroSky Mobile device must be connected to an external device supporting Bluetooth connectivity. This connection allows for seamless communication between the NeuroSky Mobile device and the external device, facilitating data transmission and enabling the analysis and processing of EEG signals and brainwave data.. The Think Gear Android API reduces the complexity of managing connections and handles analyzing the data stream from the EEG headset. This enables applications to respond to the wearer's mental activity, allowing for personalized and context-aware experiences. [54].

4. NeuroSky Experimenter NeuroSky

Experimenter is a free application on NeuroSky store which allows extraction of brain waves and EEG features like the frequency bands, attention, and meditation, for visualization, analysis, and data generation. It is being used for interfacing with the NeuroSky Mindwave device and logging the processed frequency bands data of users.

5. Python and Jupyter Notebook

Python is a widely used high-level programming language known for its versatility, particularly in machine learning and data science applications. For this research, we will leverage the power of Python in conjunction with Jupyter Notebook, an interactive data science environment that facilitates both programming and documentation tasks. This combination enables us to apply machine learning algorithms seamlessly, train models using various classifiers, and analyze the results. We will employ Flask, a Python web framework, to deploy the trained models and create API endpoints. Python scripts developed and tested in Jupyter Notebook will be utilized alongside Flask to build the necessary infrastructure for model deployment and API integration. This combination of Python, Jupyter Notebook, and Flask empowers us to efficiently develop, test, and deploy machine learning models while providing a user-friendly interface and web-based functionality.

6. Pandas

Pandas is an open-source Python package renowned for its robust data analysis and manipulation capabilities.

Widely utilized in the industry for Data Science tasks, Pandas offers an extensive array of functionalities for handling and manipulating tabular and time series data. This is achieved through versatile data structures such as data frames and series. Pandas played a crucial role in storing and efficiently manipulating tabular data comprising EEG values in this study. Its rich features and intuitive syntax made it an ideal choice for managing and analyzing the EEG dataset.

7. Scikit Learn and Machine Learning Model

Scikit-learn is a well-liked open-source Python package for Machine Learning and predictive analytics. It offers various functionalities for classification, regression, clustering, dimensionality reduction, model selection, and preprocessing. In the research, scikit-learn was used for data preprocessing and classification tasks.

8. Matplotlib and Seaborn

Matplotlib is a widely used Python package offering extensive data visualization and plotting capabilities. It encompasses features for creating static, interactive, and animated plots, providing users with flexibility and control over their visualizations. While Seaborn is a data visualization toolkit constructed atop of Matplotlib. It provides a high-level interface, allowing users to easily generate visually appealing plots and graphics. In the study, Matplotlib and Seaborn were utilized for plotting purposes and conducting Exploratory Data Analysis (EDA) to gain insights from the data. These libraries offered valuable tools for visualizing the data and effectively communicating its patterns and relationships.

9. Sklearn Porter

Sklearn Porter is a freely available library that converts trained Sklearn Machine Learning models from Python into code files compatible with languages such as Java, C, and JavaScript. This functionality facilitates the deployment of models on embedded systems and mobile devices the Sklearn Porter for Android was specifically used to convert an MLP Neural Network model, trained with Sklearn, into a Java class. The converted Java class was subsequently integrated into the Android codebase. Additionally, enhancements were made to the code to improve its usability, and new features, including standardization, were implemented to enhance the system's overall functionality.

10. Android Studio and Mobile App

Android, developed by Google, is an extensively used mobile platform renowned for its robust development framework and an open marketplace that enables the seamless distribution of apps to users. It offers developers powerful tools and features for developing, debugging, and packaging applications. With a fully integrated environment dedicated to application development, Android empowers users to harness advanced capabilities and create innovative mobile experiences. Its popularity stems from its comprehensive ecosystem, allowing developers to build and deploy various applications to Android users worldwide.

11. Firebase Cloud Database

Cloud Firebase is a scalable and flexible NoSQL database. It can be used for mobile apps, server-side and web development. It stores and syncs the data and makes it easy to use in mobile apps. Cloud Firebase was used in our app to upload the EEG data of users. Accounts of users were created, and data was uploaded after login.

EXPERIMENTS AND RESULTS

This section discusses implementing the designed system for detecting and classifying depression through EEG. The NeuroSky Mindwave mobile device collects EEG signal data via Bluetooth and the NeuroSky APIs. Data collection is performed using the Neuro Experimenter app. Initially, MATLAB was used but later replaced by the Neuro Experimenter app for its ease of use and accuracy. The collected data is regularly sampled over a specified duration and used for prediction and training. The Machine Learning model aims to classify EEG signals into different levels of depression, with predefined classes:

1. Minimal Depression
2. Moderate Depression
3. Severe Depression

The data in this study were labelled by associating depression states with a specific group of individuals. A mental health test [72] based on a set of questions was utilized to obtain a depression state score for each participant. The participants indicated that their mental state aligned with the test results. To facilitate classification, the test scores were divided into three categories representing different depression state classes. The individuals who contributed to the data collection process were a team member's friends, relatives, and family members, and the data was collected at the team member's residence. Data of 30 people was used and around 300 measurement samples were collected. The data distribution was imbalanced but not too much. 178 samples were of minimal depression, 59 were of severe depression and 61 were moderate depression. Figure 14 shows the data distribution of depression levels.

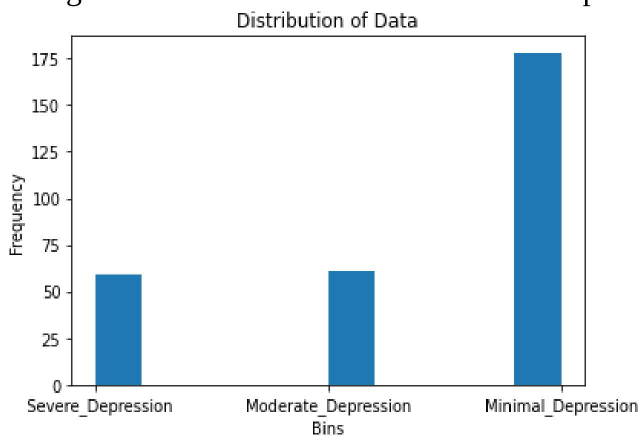

Fig 4. Data distribution of Depression levels

C. DATA PREPROCESSING AND FEATURE EXTRACTION

NeuroSky Mindwave senses the EEG brainwaves using a single electrode and communicates that data to a computer or mobile using Bluetooth. The data is in the representation of voltage readings, like most sensors. The EEG voltage forms a time domain signal.

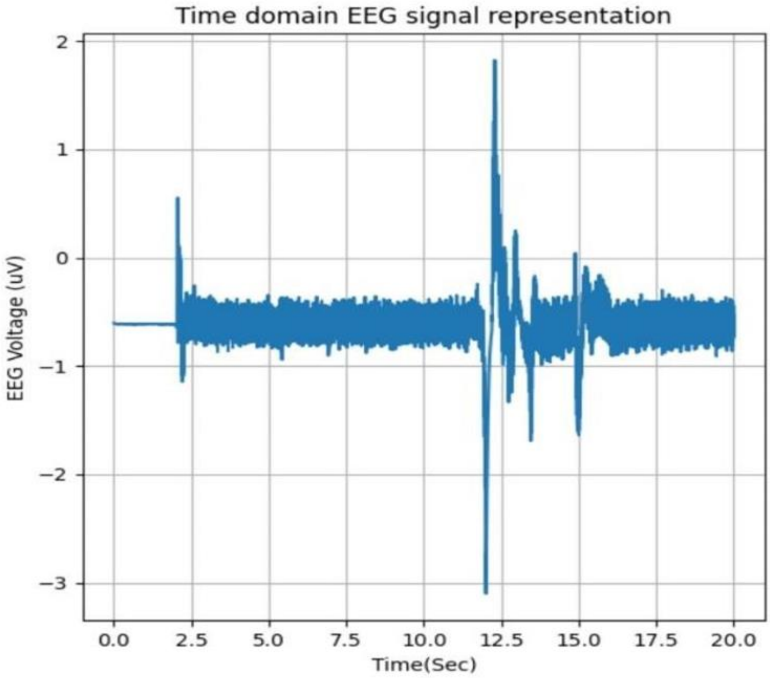

Fig 5. Signal in Time Domain

The time domain signal is undergoes transformation to the frequency domain to determine the observe maximum magnitude lying at a specific frequency value of the activity.

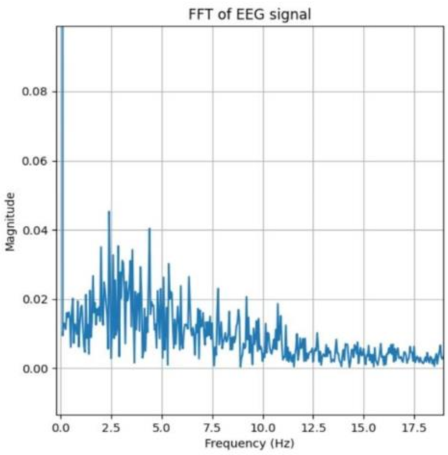

Fig 6. Signal in Frequency Domain

To transform a signal from the time domain to the frequency domain, we used Fast Fourier Transform (FFT) function. This conversion to frequency domain helps us determine the corresponding frequency to a specific activity. We can observe the maximum magnitude lying at a specific frequency value of the particular activity. The conversion formula for transforming raw values to voltage is given by:

$$\mathbf{V(Volts)} = \frac{\mathbf{Raw\ Value\ (1.8/4096)}}{\mathbf{200}}$$

Equation 1. Formula for Raw values to Voltage

The NeuroSky device has its range for the initial raw value based on the chip and equation 1 is from NeuroSky documentation to calculate the true voltage. 4096 are the possible values that 4-bit ADC exhibits, from which the data is being recorded. The EEG features that are being used to develop the

Machine Learning model are frequency band values. Fourier Transform is used to decompose the time-domain EEG signal into different frequency ranges, which are called Alpha, Beta, Gamma, and Theta waves. These frequency bands are commonly used in EEG based models. They seem particularly suitable for our application because the different bands represent mental states, as shown in Figure 17, which relate to symptoms related to depression such as Delta is related to loss of body awareness, Beta is related to anxiety, disease, and feeling of separation, Theta is related to emotional experiences and Alpha relates to relaxation.

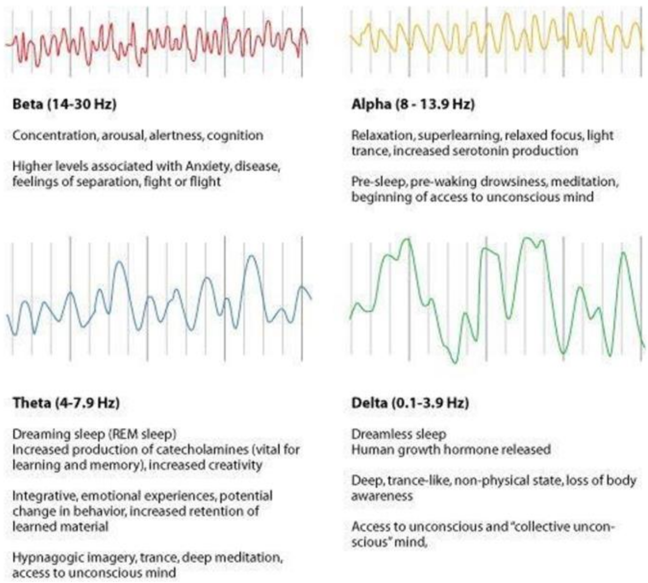

Fig 7. Brain wave Frequency chart

EEG frequency bands have been used in mental state analysis including depression for a long time. Research on EEG for depression analysis [55] indicates that EEG frequency band values relate to depression e.g. depressed patients had elevated Beta and Alpha, while Theta and Delta also distinguished the control group of depressed patients with non-depressed people. The relation of Alpha band symmetry and elevation with depression has been studied in several works of research [56] [57] Neuro Experimenter gives data in the form of the power of each wavelet. The activities were performed for 2 minutes each to obtain enough values. 1 value for each wavelet was obtained. The class had to be manually labeled after collecting each dataset. The sample dataset is provided in the figure shown below. Alpha1 is Alpha High which stores all the high frequency values of the Alpha wave. Alpha2 represents Alpha Low which has all the low frequency values of Alpha wave. Similarly, Beta1 stands for Beta High and Beta2 represents Beta Low. Gamma1 is Gamma Mid and Gamma2 is Gamma Low.

Figure 18 shows raw data collected from EEG device were converted into different bands using Neuro-Experimenter application which is connected to NeuroSky Mindwave2.0 i: e Alpha1, Alpha2, Beta1, Beta2, theta, Gamma1, Gamma2, Delta.

1	Delta	Theta	Alpha1	Alpha2	Beta1	Beta2	Gamma1	Gamma2	class
2	516896	30558	3907	9751	9627	2274	6003	3108	Severe_Depression
3	804673	17161	197	1514	1433	684	259	64	Severe_Depression
4	1260034	135658	94619	31565	14456	18915	6600	2683	Severe_Depression
5	776943	243275	56294	111868	29948	10958	5830	3533	Severe_Depression
6	308015	201750	12551	3621	10786	14554	13041	12269	Severe_Depression
7	1930647	403531	28715	26740	29638	22856	20765	10299	Severe_Depression
8	54073	42845	5010	7450	5678	3505	4299	1954	Severe_Depression
9	49692	28104	14316	6796	10433	5510	3784	2289	Severe_Depression
10	1589797	501280	35130	24169	9843	14639	8543	1483	Severe_Depression
11	76096	8682	973	954	1367	677	328	383	Severe_Depression
12	376491	575439	80794	175882	71266	25096	17683	6648	Severe_Depression
13	1999044	50922	3392	11636	11341	4802	2610	1154	Severe_Depression
14	957936	42814	9233	18344	3619	4797	2978	847	Severe_Depression
15	1200153	84344	32894	39263	39263	14010	13266	6950	Severe_Depression
16	1138064	40462	103046	22228	35013	7292	9208	2812	Severe_Depression
17	666166	60472	41199	8730	23973	2791	3436	2006	Severe_Depression
18	1461682	74647	5388	20924	7608	5897	6772	2591	Severe_Depression
19	2782283	219248	17222	121693	28802	21470	6670	16033	Severe_Depression
20	625928	16209	4895	1324	1638	786	893	330	Severe_Depression
21	120701	14035	4556	1748	2454	1316	1072	472	Severe_Depression
22	1117585	27458	24246	10184	3499	2173	2075	1074	Severe_Depression

Fig 8. CSV file with different class labels

D. DATA ANALYSIS

Exploratory Data Analysis (EDA) was conducted on the dataset comprising EEG frequency bands. This analysis aimed to examine the relationship between EEG frequency band values and depression classes, as well as their interrelationships, feature importance, and class separability. Various visualizations were employed to facilitate the analysis, including pair plots, boxplots, correlation heatmaps, and bar charts illustrating feature importance. These plots provided insights into the patterns, distributions, and correlations within the dataset, aiding in the understanding of the underlying relationships between EEG frequency bands and depression classes.

Fig 9. Bar charts of Feature Extraction

In Figure 9, a Seaborn Pair-plots visualization is presented. This plot showcases scatter plots of various feature pairs for bivariate analysis, accompanied by KDE plots depicting a feature's probability densities across different classes. It is evident that while there may be some overlap in feature values between various classes, there exists a significant separation within the classes, particularly between the minimal depression and depression classes, as well as for specific pair of two features. This observation suggests that a Machine Learning classifier can achieve reasonably accurate classification. However, it is essential to note that the decision boundary may not necessarily be linear. Additionally, side-by-side boxplots were employed for comparison of the ranges and medians of features across different classes, providing further insights into their distributions and variations.

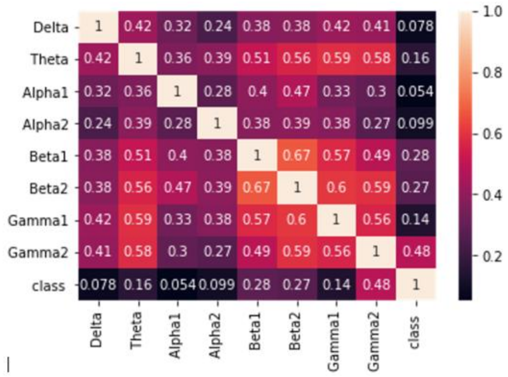

Fig 10. Correlation Heatmap [77]

After label encoding the classes as 0, 1, and 2, the plot reveals correlations between the frequency band values, although not to an extent that renders the features redundant. Notably, the 1 and 2 bands, corresponding to Beta1 and Beta2 frequencies, exhibit a certain degree of correlation. Moreover, Beta and Gamma2 frequencies demonstrate a significant correlation with the encoded class labels.To analyze the significance of various frequency bands in predicting the depression state and identify capable features for choice, various tests were conducted for feature selection and feature importance. These tests encompassed the following methodologies:

- The SelectKBest method in Scikit-learn was employed for feature selection, utilizing univariate statistics to identify the K best features. It utilizes the Chi-Squared test to assess the independence of each feature from the output.
- Recursive Feature Elimination (RFE) is a wrapper method that iteratively eliminates features and evaluates their impact on the prediction using a chosen model. In this study, the Support Vector Classifier was utilized as the underlying model for RFE.
- The ExtraTreeClassifier feature importance method was employed, which constructs an ensemble of decision trees and assigns importance to features based on their contribution to splitting the data at the branches of the trees. The feature importance results were consistent across all methods, with Delta, Theta, Gamma2, and Beta2 frequencies appearing to be the most significant features. No features exhibited exceptionally low importance, and no feature reduction was performed during the model training process.

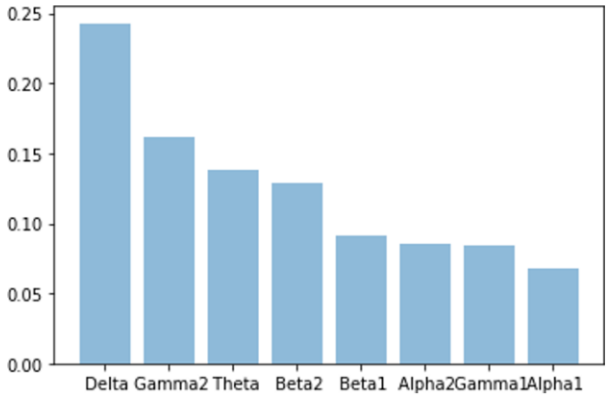

Fig 11. Decision tree Ensemble Bar Graph

The box plot presented below illustrates the distribution of the most important feature related to the Delta band. It is evident from the plot that the minimal depression class exhibits a substantially lower median value for the Delta band compared to the depressed classes.

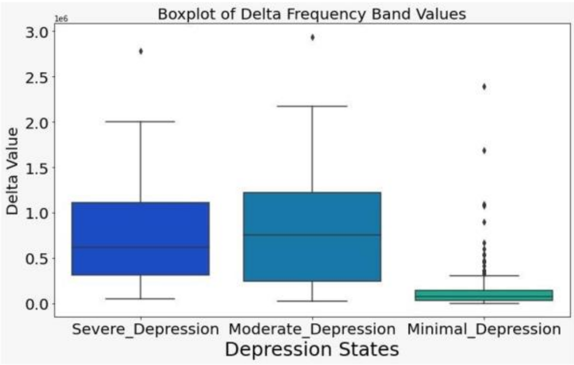

Fig 12. Box plot of Delta Feature

E. MACHINE LEARNING ALGORITHMS

Various Machine Learning classification models were trained and evaluated in this study, including Logistic Regression, Support Vector Classifier, Decision Tree, K-NN, Random Forest, and a Multi-Layer Perceptron (MLP) Neural Network. The MLP Classifier was chosen as the final mobile deployment model, with two hidden layers of sizes 12 and 4. The accuracy achieved by the final model was 93%.To prepare the target column for training with Machine Learning algorithms, it was encoded using Label Encoding, converting the class labels into numeric values (0, 1, and 2). This encoding was applied because there are only three classes, which also possess an ordinal nature. Feature scaling is crucial for many Machine Learning algorithms, as it aids in gradient descent convergence and improves the utilization of features for distance-based calculations. To achieve this, the Standard Scaler technique was employed for standardizing the feature values. This process involves subtracting the feature mean from each value and dividing it by the standard deviation, resulting in scaled data with unit variance. Hyper-parameter tuning was performed to identify the optimal hyper-parameters for training each specific Machine Learning model. Grid Search was utilized to assess models using various hyper-parameter values and determine the best combination for performance optimization. The dataset was split into 85% for training and 15% for validation, following a random shuffling process, ensuring that the data is representative and provides a reliable evaluation of the models.

Following are the description of the Machine Learning algorithms that were experimented during this research:

a. Logistic Regression

Logistic Regression is a linear classification model. It predicts a likelihood using the S-shaped logistic function, also called sigmoid. The model is represented by an equation and the parameters i.e. weights and biases are learned during training, using maximum likelihood. [58]

b. Support Vector Machine

Support Vector Machine (SVM) is a widely used Machine Learning algorithm suitable for classification and regression tasks. The Support Vector Classifier, based on SVM, was employed in this study. The concept of SVM involves mapping the feature vectors of observations into a higher-dimensional feature space. The objective is to find an optimal hyperplane that maximizes the margin, or distance, between points of different classes. By utilizing the support vectors and maximizing the margin, SVM aims to create a decision boundary that separates different classes. This distance-based approach makes SVM particularly useful in scenarios where clear separation between classes is desired.

c. Decision Tree

The Decision Tree algorithm is a tree-based model where feature values are evaluated at each split, acting as decision rules. Decision Trees are versatile and can be used for classification and regression tasks. During the prediction process, the tree traversal starts from the root node and progresses towards the leaf nodes, selecting the appropriate path based on the checks performed at each split. The final prediction is made at the leaf node reached through this process. This mechanism allows Decision Trees to make predictions by following a sequence of feature-based decisions.

d. Random Forest

The Random Forest Classifier is an ensemble algorithm built upon Decision Trees' foundation. It involves constructing multiple Decision Trees with some level of randomness in the splitting process. The predictions of these individual trees are then combined through a voting mechanism to determine the final prediction. One of the key advantages of the Random Forest Classifier is its ability to mitigate overfitting, a common issue encountered with standalone Decision Trees. By aggregating the predictions from multiple trees, the classifier ensures a more robust and reliable prediction outcome.

e. K-Nearest Neighbors

The K-Nearest Neighbors (K-NN) algorithm is an instance-based Machine Learning model that does not require prior training. Instead, it retains all the examinations and provides estimations at runtime by evaluating the similarity between the input data and the stored observations. In classification tasks, K-NN determines the output category of a new feature vector by counting how many of its K most similar examples belong to each class. The category with the highest count among the closest examples is chosen as the prediction. For regression tasks, instead of counting, K-NN calculates the average of the target values of the K nearest neighbours leveraging the proximity of data points, K-NN can make predictions without relying on explicit model training.

f. Neural Network

Neural Networks are a powerful Machine Learning model composed of interconnected layers of computational units known as perceptron. These networks can learn intricate hierarchical patterns and capture complex non-linear relationships among features. Neural Networks can be employed for both classification and regression tasks. Each perceptron within a Neural Network receives inputs from other nodes, which are then aggregated using parameters known as weights and biases. The resulting value is then passed through an activation function, such as the sigmoid function commonly used in logistic regression.

Deep Learning is about using Neural Nets with many hidden layers that could represent complex models. Deep Learning has done wonders in recent years due to new research 49 and hardware. If a large amount of training data is available, then Deep Neural Networks often outperform other ML techniques. There are many variations of Neural Networks architectures that work great for specific tasks e.g. CNNs for Computer Vision and RNNs for Text and Sequences.

F. ANDROID APP DEVELOPMENT

The Android App is being used for Machine Learning model inference and results display on mobile as well as for uploading user data into a cloud database. The app has modules related to handling user accounts and login, processing the input data, running inference on Machine Learning model and uploading data to cloud.

G. RESULTS

This includes the results obtained using MATLAB, Neuro-Experimenter, Android Studio and database server.

Processed Data Figure 12 Displays a random sample of the training data following the processes of sampling, feature extraction, label encoding, and standard scaling standardization:

The '1' class represents Minimal depression, '2' class represents Moderate depression, '3'represents Severe Depression.

	Delta	Theta	Alpha1	Alpha2	Beta1	Beta2	Gamma1	Gamma2	Depression State
212	-0.390539	-0.483791	0.264559	0.251776	-0.309648	0.178635	0.037301	-0.551798	1
104	1.508125	1.676188	0.492697	2.550215	1.266099	1.565351	1.723524	1.370917	2
280	-0.651726	-0.394704	-0.112874	-0.114048	-0.554687	-0.680308	-0.943018	-0.646640	1
196	-0.082423	-0.100315	-0.421042	-0.403673	-0.047031	-0.391356	0.590382	-0.479112	1
216	-0.647214	-0.226041	-0.360757	-0.362358	-0.520366	-0.161852	0.657277	-0.342362	1
129	-0.397389	-0.549964	-0.560308	-0.521466	-0.463149	-0.284959	2.720474	0.419485	1
1	0.735203	-0.579811	-0.890038	-0.996625	-0.891132	-0.954398	-1.083644	-0.737272	0
269	-0.353154	-0.269499	-0.035815	-0.064624	-0.269570	-0.437346	-0.806826	-0.669599	1
172	-0.716040	-0.623997	-0.587392	-0.578161	-0.067114	-0.129393	0.131175	0.524052	1
244	-0.718739	-0.642347	-0.226384	0.139680	-0.097216	-0.751658	-0.869101	-0.657468	1

Fig 12. Sample of Training Data

Numeric labels have been assigned to represent different states of depression. Specifically, the minimal state of depression is denoted by the numeric value 0, the moderate state of depression is represented by the numeric value 1, and the severe state of depression is indicated by the numeric value 2.

H. MACHINE LEARNING MODELS EVALUATION

The Machine Learning problem addressed in this study involved multiclass classification. Several metrics were employed to analyze the classification models' performance, including Accuracy and weighted F1-Score. Accuracy represents the proportion of accurate predictions from the count of predictions made. However, since our dataset exhibits class imbalance and involves multiple classes, weighted F1-Score was chosen as the primary metric for comparing algorithm performance. Weighted F1-Score is a suitable metric in such scenarios, as it considers precision and recall for each class, and provides a balanced assessment by considering class frequencies. Precision reflects the accuracy of a model's predictions, precisely the proportion of correct optimistic predictions out of all positive predictions. It is calculated as the ratio of True Positives (correct detections) to the total number of optimistic predictions.

$$\textbf{Precision} = \frac{\textbf{True Positive}}{\textbf{True Positive + False Positive}}$$

Equation 2. Sample Precision for True Positive

Recall, also referred to as sensitivity or the true positive rate, quantifies the fraction of genuine positive cases correctly recognized by a model. It indicates the model's ability to avoid missing positive detections. Mathematically, recall is computed by dividing the number of True Positives by the sum of True Positives and False Negatives. It provides insights into how well a model captures and detects actual positive cases, minimizing the chances of false negatives.

$$\textbf{Recall} = \frac{\textbf{True Positive}}{\textbf{True Positives + False Positives}}$$

Equation 3. Recall for True Positive

F1 Score considers both precision and recall equally in evaluation.

$$\textbf{F1 Score} = \frac{\textbf{2* Precision * Recall}}{\textbf{Precision + Recall}}$$

Equation 4. To calculate F1 score

Both Precision and Recall play crucial roles in our application. High Precision ensures that if the model predicts depression and encourages someone to seek diagnosis and assistance, the individual is more likely to genuinely have depression. On the other hand, high Recall ensures that the model minimizes the chances of missing individuals with depression who require mental health support. Precision and Recall can be calculated for specific classes, focusing only on detecting that particular class within the formula. For multiclass classification problems, direct computation of the F1-Score is not possible. However, individual F1-Scores can be calculated for each class using Precision and Recall values. An aggregated F1-Score for a multiclass classification model can be obtained by taking the mean or weighted mean of the individual class F1-Scores. The weighted F1-Score, which considers the class sample sizes as weights, is particularly robust against class imbalance. Hence, it was chosen as the metric for ranking the models in this study. In

the training and testing process, 85% of the data was utilized for model training, while the remaining 15% was used for testing. The data were randomly shuffled to ensure a representative distribution across both sets.
Following is the F1 and accuracy score of KNN, and same for all models:

```
model = KNeighborsClassifier(n_neighbors=7) model.fit
(x_train, y_train) print ('Acc', model. score (x_test, y_test))
print ('F1:', f1_score(list(y_test), list (model.
predict(x_test)),average='eighted'))
Random Forest
model = RandomForestClassifier (n_estimators=50,
random_state=0)model.fit (x_train, y_train) print ('Acc',
model. score (x_test, y_test))
print ('F1: ', f1_score(list(y_test), list (model.
predict(x_test)),average='weighted'))
model = LogisticRegression () model.fit (x_train,
y_train) print ('Acc', model. score (x_test,
y_test))
print ('F1:', f1_score(list(y_test),list(model. predict
(x_test)), aveage='weighted'))
```

Following table shows the comparison of evaluation results for the Machine Learning models:

ML Model	Accuracy	Weighted F1-Score
Neural Network	0.933	0.932
Random Forest	0.911	0.908
Support Vector Machine	0.888	0.881
Decision Tree	0.844	0.835
K-Nearest Neighbors	0.855	0.828
Logistic Regression	0.844	0.826

Table 1. Comparison of Evaluation Result of Machine Learning Model

The findings reveal that the Neural Network performed best among the tested models. Although Random Forest and SVM also demonstrated strong performance, the remaining models showed notably lower performance. This suggests that the data comprises substantial non-linear relationships between frequency band values and depression states, favoring the effectiveness of non-linear models despite the limited data availability. This observation aligns with the intuitive understanding and partially supports the data analysis.
The Neural Network architecture we developed was intentionally kept small and shallow, considering the limited training data. Remarkably, it delivered promising results. While the accuracy and weighted F1-Score values were pretty similar, it is worth noting that the F1-Score metric ranked the Decision Tree higher than K-NN, despite the latter having a higher accuracy.
Confusion Matrix was also plotted, which seems perfect except for 3 samples, where minimal and severe depression were confused and misclassified.

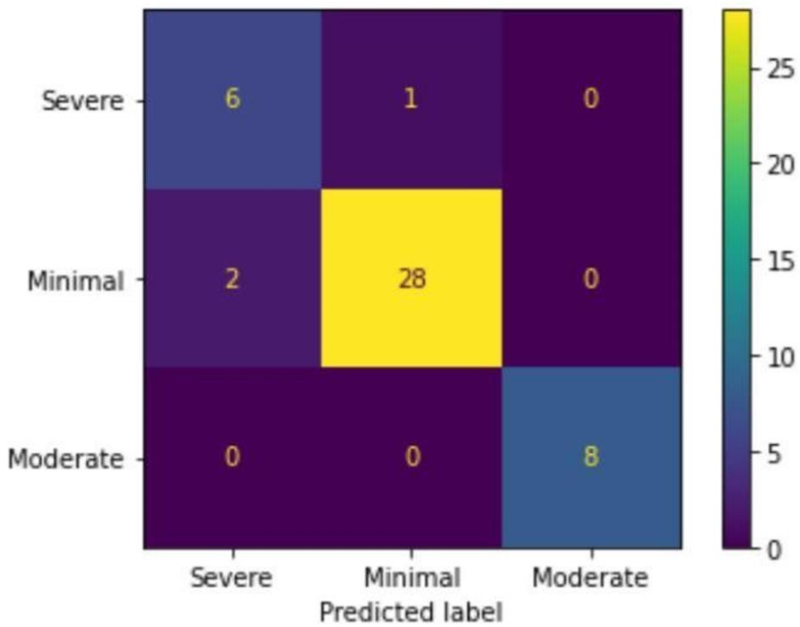

Fig 13. Confusion Matrix

CONCLUSION

In this study EEG data was collected and analyzed to estimate depression states, construct predictive models, and developing a mobile app. The collected data were categorized into three main classes according to their depression test score for model training. Time and Frequency domain analysis were performed to see the behaviour of brain waves signal. The time domain signal is converted to the frequency domain to determine the maximum magnitude lying at a specific frequency value of the activity. Data was decomposed into 8 steps. These steps represent different bands i:e Alpha1,Alpha2,Beta1,Beta2, Gamma1,Gamma2, Delta, Theta. A literature review was conducted to assess the feasibility and applicability of utilizing EEG for depression and mental health analysis. Additionally, exploratory data analysis was executed on the EEG features, yielding valuable insights into the dataset. Supervised Machine Learning algorithms were applied for the classifications and model were trained, evaluated and compared. A pipeline for data collection and processing was designed. The Machine Learning Model then deployed into the mobile application. A mobile app was developed that allows user interaction and classifies EEG signals into depression states, while also uploading the data of users on Database for future use. Compared to other studies, a single electrode is used in our system, thereby making it more portable and convenient, and minimizing the amount of data considerably.

The system serves as a brain-computer interface and EEG-based test to assess the level of depression prior to clinical diagnostic tests. Additionally, it can be utilized for regular monitoring of individuals with mental health concerns.

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