Detection of Anxiety Disorder using EEG Signals

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DECLARATION BY STUDENT

I hereby declare that the data presented in this Dissertation report entitled, "Detection of Anxiety Disorder using EEG Signals" is based on the results of investigations carried out by me in the Electronics Department at the School of Physical and Applied Sciences, Goa University under the Supervision of Prof. Rajendra S. Gad and the same has not been submitted elsewhere for the award of a degree or diploma by me. Further, I understand that Goa University or its authorities will be not be responsible for the correctness of observation / experimental or other findings given the dissertation.

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COMPLETION CERTIFICATE

This is to certify that the dissertation report "Detection of Anxiety Disorder using EEG signals" is a bonafide work carried out by Ms. Saloni Bhikaji Mandrekar under my supervision in partial fulfilment of the requirements for the award of the degree of Master of Science in the Electronics Discipline at the School of Physical and Applied Sciences, Goa University.

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PREFACE

This project looks at the classification of a subject's anxiety level while using virtual reality (VR) stimuli using an EEG signal. This study's primary goal is to examine the cognitive stress experienced by 42 participants (8 men and 34 women) having the age between 22yrs to 45yrs, who are split into 2 groups (20 healthy controls and 22 anxious). Data were gathered using five distinct data acquisition protocols. Using an EEG head cap device, the subjects' EEG signal is continually monitored.

EEG is The non-invasive techniques for diagnosis are rapidly increasing due to technological advancement in medicine. The analysis of physiological signals reveals information about the state of human health. (EEG) is commonly used in neuroscience for a wide range of operations that acquire electrical activities of brain. EEG has been found to be useful in a number of clinical applications.

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ABBREVIATION USED

Entity	Abbreviation
Electroencephalogram	EEG
Generalized Anxiety Disorder	GAD
Social Anxiety Disorder	SAD
Acute Distress Disorder	ASD
Post Traumatic Stress Disorder	PTSD
Panic Disorder	PD
Agoraphobia	AP
Diagnostic and statistical manual of mental disorder	DSM
Cognitive behavioral therapy	CBT
Machine learning	ML
Wavelet transform	WT
Support vector machine	SVM
Convolutional neural network	CNN
K - Nearest Neighbour	KNN
Naïve Bayes	NB
Long short term memory neural network	LSTM
Deep neural network	DNN

ABSTRACT

Stress, sadness, and worry are major concerns during adolescence since it's a critical time in life. Extended periods of stress are among the risk factors that might lead to suicidal thoughts, destructive ideas, and alcohol and drug dependence in later life.

Brain activity can be recorded using an electroencephalogram (EEG). The test is painless, and tiny sensors are applied to the scalp to detect electrical impulses generated by the brain. This project looks at the classification of a subject's anxiety level while using different stimuli using an EEG signal. An EEG headset is used in conjunction with an acquisition process that alternates between calming and tense situations in order to track the subject's psycho-physical state. This study's primary goal is to examine the cognitive stress experienced by 42 participants (8 men and 34 women) having the age between 20 years to 50yrs, who are split into 2 groups (20 healthy controls and 22 anxious). The data was collected in the dark room away from the external disturbance, the laptop screen was placed at the distance of 80 cm at the viewing angle of the participants. Data were gathered using five distinct data acquisition protocols. Using an R - NET EEG head cap from brain product device, the subjects' EEG signal is continually monitored. Volunteers were asked to complete questionnaires on their mood and degree of anxiety after the session. Next, the anxiety levels are classified using convolutional neural networks (CNNs) and support vector machines (SVMs), who gave the highest accuracy. Finaly the SVM model and CNN model is validated into 10-fold cross-validation (10-CV). The SVM shows highest classification accuracy of 61%.

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CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

Stress, sadness, and worry are major concerns during adolescence since it's a critical time in life. Extended periods of stress are among the risk factors that might lead to suicidal thoughts, destructive ideas, and alcohol and drug dependence in later life. According to data from the National Crime Records Bureau, more than 2320 youngsters in India commit suicide each year as a result of failing exams. This increased figure illustrates how serious this problem is and how much of an influence it has on society.

A disagreeable condition of internal turmoil and emotions of dread about future occurrences are characteristics of the emotion known as anxiety. Anxiety is a widespread and unfocused sensation of unease and worry caused by an overreaction to a circumstance that is only seen as dangerous by the individual. In addition to exhaustion, nausea, tightness in the abdomen, difficulty breathing, tense muscles, restlessness, and difficulty concentrating are frequently present.

Fear is the fight-or-flight reaction to an actual or perceived immediate threat. Anxiety, on the other hand, is the expectation of a threat in the future, including dread. Anxious people tend to avoid situations that they have previously felt anxious about. Anxiety is a common response to pressure. In certain circumstances, modest anxiety levels might even be advantageous. It can warn us of impending risks and assist us in being attentive and ready. Excessive dread or anxiety is a feature of anxiety disorders, which are distinct from typical emotions of apprehension or worry. Among mental problems, anxiety disorders are the most prevalent. Almost thirty percent of individuals experience them at some time throughout their life.

Anxiety differs from fear in that anxiety is the expectation of a potential threat, whereas fear is the emotional reaction to an actual threat. Nervous behaviors like pacing back and forth, physical complaints, and ruminating are frequently present along with it. Nonetheless, a variety of psychotherapy interventions can be used to treat anxiety problems. Most people benefit from treatment and have regular, productive lives. The Anxiety and Depression Association of America (ADAA) estimates that 40 million or more Americans suffer from an anxiety condition. It is the most prevalent category of mental diseases in the nation. But only 36.9 % of those suffering from anxiety disorders are given therapy.

1.2 FEAR VS ANXIETY

Fear is a proper emotional and cognitive reaction to a perceived threat; anxiety is not the same as fear. In the distinct behaviors of escape, defense, and fight-or-flight reactions are associated with anxiety. According to David Barlow, anxiety is "a future-oriented mood state in which one is not ready or prepared to attempt to cope with upcoming negative events" . He further states that anxiety and fear are distinguished by the difference between risks that are present now and those that are future. Anguish, fear, panic, or even apprehension are additional terms for worry. Anxiety is defined in positive psychology as the emotional state that arises from a challenging situation for which the individual lacks adequate coping mechanisms.

Fear and anxiety can be differentiated into four domains:

- duration of emotional experience,
- temporal focus,

- specificity of the threat, and
- motivated direction.

Fear is transient, focused on the here and now, directed at a particular threat, and it helps one flee from it. Conversely, anxiety promotes overly cautious behavior when confronting a potential threat, is long-acting, future-oriented, generally targeted towards a diffuse threat, and gets in the way of helpful coping.

1.3 ANXIETY AND ANXIETY DISORDER

Anxiety is a multifaceted reaction to perceived or actual dangers. Changes in cognition, body, and behavior may be involved. The brain releases adrenaline, a hormone and chemical messenger, in response to actual or imagined threat, which sets off these anxiety-inducing reflexes known as the fight-or-flight response. This reaction can happen to certain people in socially awkward settings or when significant decisions or events are happening.

Sometimes, the length or intensity of anxiety symptoms might differ significantly from the initial stressor event trigger. It's also possible for physical symptoms to appear, such nausea and elevated blood pressure. These reactions elevate anxiety to the level of an anxiety disorder.

Anxiety may become disruptive to day-to-day functioning if it reaches the stage of a disorder. People with anxiety disorders may attempt to avoid circumstances that exacerbate or trigger their symptoms. Personal connections, academic performance, and professional performance may all be impacted. Generally speaking, fear or anxiety must meet certain criteria in order to be labeled as an anxiety disorder: Be excessive for the circumstances or age; impede their capacity to operate normally.

1.4 SYMPTOMS OF ANXIETY DISORDER

Symptoms vary depending on the type of anxiety disorder you have. General symptoms of an anxiety disorder include:

1. Physical Symptoms:
   - Cold or sweaty hands.
   - Dry mouth.
   - Heart palpitations.
   - Nausea.
   - Numbness or tingling in hands or feet.
   - Muscle tension.
   - Shortness of breath.

2. Mental Symptoms:
   - Feeling panic, fear and uneasiness.
   - Nightmares.
   - Repeated thoughts or flashbacks of traumatic experiences.
   - Uncontrollable, obsessive thoughts.

3. Behavioral Symptoms:
   - Inability to be still and calm.
   - Ritualistic behaviors, such as washing hands repeatedly.
   - Trouble sleeping.

1.5 CAUSES OF ANXIETY

A mix of environmental and genetic variables could be involved, according to the National Institute of Mental Health (NIMH)Trusted Source. Another theory being researched is brain chemistry. There may be involvement in the brain regions that regulate your fear response.

Two more mental health conditions that can coincide with anxiety disorders are depression and substance abuse. In an effort to lessen their worry, many people turn to alcohol or other drugs. These medications provide a brief relief from their symptoms. Alcohol, nicotine, caffeine, and other drugs can exacerbate anxiety problems.

Experts speculate that a number of variables, including genetics and social stress, are at play.

Twin studies imply that genetics could be involved. For instance, a study published in PloS ONE Trusted Source raises the possibility that the RBFOX1 gene has a role in the emergence of disorders connected to anxiety, including generalized anxiety disorder. The authors think that there are non genetic and genetic contributing variables.

Studies are also being conducted on specific brain regions, including the hippocampus and amygdala. The little, deep-seated amygdala in the brain is responsible for processing threats. When there are indications of danger, it notifies the rest of your brain. It may cause feelings of worry and fear. It appears to be involved in anxiety disorders including phobias of certain objects or situations, such bees, cats, or drowning. The anxiety disorders may also be influenced by hippocampus region. It's a part of the brain that's used to store memories of potentially dangerous situations. Those who have fought in battle or who endured domestic violence as children seem to have less of it.

1.5.1 Stress:

Although everyone experiences stress occasionally, persistent or severe stress may increase the chance of developing chronic anxiety.

The authors of a scientific review that was published in 2019 examined the neurobiological evidence between stress and anxiety (Trusted Source). The researchers came to the conclusion that neurological traits in certain brain areas, such the amygdala, which is involved in processing inputs that generate fear and threat, may account for how stress exacerbates anxiety.

1.5.2 Genetic Factors:

If someone in the family currently suffers from an anxiety disorder, the person may be more vulnerable to developing one yourself. Growing data indicates that genetic features may play a role in addition to the effects of social and economic factors.

A 2019 study looked at the connections between stress- and anxiety-related disorders and genetic characteristics. The scientists' conclusion was that having certain inherited characteristics might increase the risk of developing anxiety. These characteristics might be inherited.

1.5.3 Personality Type:

Certain personality traits may influence how susceptible person is to anxiety and anxiety disorders.

A team of researchers watched 489 first-year college students for six years in order to investigate into the possible impacts of different perspectives on the emergence of anxiety and depression. These included an in introversion. They found that those who as young adults experienced a great deal of negative thoughts and emotion, were very critical of themselves, had trouble accepting criticism, or were highly self-critical were also more likely to develop major depressive disorder, panic disorder, agoraphobia, and generalized anxiety disorder (GAD). Certain traits in the personality may make more or less susceptible to anxiety and anxiety disorders.

1.5.4 Trauma:

A stressful event, whether recent or old, such as being mistreated or fighting in a war, can make anxiety worse. It could also happen if the person is close to someone who has suffered trauma or if the person have witnessed something horrifying.

Acute distress disorder, often known as anxiety, is a typical response to an unexpected or frightening incident (ASD). On the other hand, PTSD, or post-traumatic stress disorder, may be indicated by chronic symptoms. The symptoms usually appear three months after the occurrence, although they may appear months or even years later.

They include:

- Flashbacks
- Bad dreams
- Feeling constantly on edge
- Difficulty sleeping
- Angry outbursts
- Avoiding places or situations that could trigger stress symptoms

1.5.5 Racism:

Even after accounting for hereditary characteristics, those who encounter racial prejudice are more likely to develop anxiety and anxiety disorders. Black people and Indigenous People of Color are particularly vulnerable to race-based traumatic stress injury (RBTS) in the United States, according to Mental Health America (MHA).

1.5.6 Gender Dysphoria

When someone has gender dysphoria, their gender identity and the gender they were assigned at birth do not correspond. This might cause chaos and distress, but it can also make you more likely to have disagreements with others around you, particularly if those people have inflexible ideas about what roles men and women should play in society.

Gender Dysphoria are at risk of:

- Anxiety and anxiety disorders
- Depression
- Thoughts of suicide
- Substance use

1.5.7 Medical Causes:

There are various ways in which a person's health can contribute to stress, such as:

- Past and present experience of mental and physical well-being
- Having a chronic illness that poses challenges to daily living
- Having a disease that causes very challenging symptoms, such as palpitations

- Having a condition where anxiety is a symptom, such as a hormonal imbalance

1.5.8 Life Events

As with trauma, life events can increase the risk of stress and anxiety.

Examples include:

- Losing a loved one
- Divorce or separation
- Spending time in the criminal justice system
- Injury or illness
- Financial pressures or a loss of employment
- Major changes, such as moving in a new house or getting married
- A person can experience these events without developing an anxiety disorder, although some may do so.

1.5.9 Medications:

Some drugs can cause anxiety as a side effect, or they may cause symptoms that feel like anxiety.

Examples include:

- Drugs containing caffeine, such as Excedrin Migraine, which can cause irritability
- Drugs to treat ADHD, such as Ritalin
- Corticosteroids, such as dexamethasone

- Some asthma medications, such as fluticasone-salmeterol (Advair Diskus), which can cause tremors
- Phenytoin (Dilantin), an anti-seizure medication
- Rytary, a drug for Parkinson's disease

1.6 TYPES OF ANXIETY DISORDER

1.6.1 Generalized Anxiety Disorder

Worry that interferes with everyday tasks and is excessive and persistent is a symptom of generalized anxiety disorder. Physical symptoms like restlessness, feeling tense or easily fatigued, difficulty concentrating, tense muscles, or trouble sleeping may be present along with this continuous stress and tension. Worries tend to center around routine issues like work obligations, family health, or smaller concerns like housework, car maintenance, or appointments.

1.6.2 Panic Disorder

The core symptom of panic disorder is recurrent panic attacks, an overwhelming combination of physical and psychological distress. During an attack, several of these symptoms occur in combination:

- Palpitations, pounding heart or rapid heart rate
- Sweating
- Trembling or shaking
- Feeling of shortness of breath or smothering sensations
- Chest pain

- Feeling dizzy, light-headed or faint
- Feeling of choking
- Numbness or tingling
- Chills or hot flashes
- Nausea or abdominal pains
- Feeling detached
- Fear of losing control
- Fear of dying

Some persons who experience a panic attack may mistakenly think they are suffering from a heart attack or another serious illness due to the severity of the symptoms. They might visit the emergency room of a hospital. Attacks of panic can be sudden and seem to happen out of the blue, or they can be predicted and happen in response to something you fear. Panic disorder typically manifests between the ages of 20 and 24. Together with other mental illnesses like depression or PTSD, panic attacks can also occur.

1.6.3 Particular Fear

Excessive and ongoing fear of a particular, usually harmless object, circumstance, or action is known as a specific phobia. Patients are unable to get over their overwhelming dread despite knowing it. Some people go to great lengths to escape their worries because they are so distressing. Examples include the fear of spiders, flying, and public speaking.

1.6.4 Agoraphobia

Agoraphobia is the fear of being in circumstances where getting out could be uncomfortable or difficult, or where there might not be someone around to help if panic attacks strike. The worry is disproportionate to the real circumstances, persists for at least six months, and interferes with day-to-day activities. A person who suffers from agoraphobia feels fear in two or more of the following scenarios:

- Using public transportation
- Being in open spaces
- Being in enclosed places
- Standing in line or being in a crowd
- Being outside the home alone

The individual needs company, deliberately avoids the encounter, or endures it while experiencing severe fear or anxiety. If left untreated, agoraphobia can get so bad that a person might not be able to leave their home. An agoraphobic may only be identified if their fear is extremely distressing or substantially interferes with their day-to-day activities.

1.6.5 Social Anxiety Disorder

When it comes to being rejected, humiliated, ashamed, or looked down upon in social situations, a person with social anxiety disorder experiences intense worry and discomfort. With this illness, a person will either attempt to avoid the circumstance or deal with it extremely anxiously. Extreme anxiety when speaking in front of an audience, interacting with strangers, or eating or drinking in public are common examples. For at least six months, the dread or worry interferes with day-to-day functioning.

1.6.6 Separation Anxiety Disorder

An individual suffering from separation anxiety disorder has overwhelming worry or anxiety when they are separated from the people they are attached to. The emotion is excessive for the person's age, lasts longer than normal (at least four weeks for children and six months for adults), and interferes with daily functioning. A person suffering from separation anxiety disorder might have dreams about being apart from the person they love the most, be reluctant to leave the house or go out at night, or be extremely concerned about losing the person they care about the most. Although physical signs of anguish might last into maturity, they often first appear in infancy.

1.6.6 Mutism of Selection

Although they communicate in other contexts, children with selective mutism remain silent in social settings like schools when it is required of them to speak. While they will talk to those in their own family while they are at home, they frequently remain silent when they are with other people, including close friends or grandparents.

Social communication may be hampered by the lack of speech, yet children with this disease may communicate nonverbally (e.g., grunting, pointing, writing). Speaking less in class might have serious repercussions as well, such as social isolation and scholastic difficulties. A great deal of social anxiety, extreme shyness, and fear of social shame are also present in many youngsters who exhibit selective mutism. They usually possess average linguistic abilities, nevertheless.

Selective mutism usually appears before the age of five, however it could not be recognized until the kid starts school. A lot of kids will grow out of selective mutism. Selective mutism may disappear in kids who also have social anxiety disorder, although the disease's symptoms can still be present.

1.7 DIAGNOSIS AND TREATMENT

1.7.1 Diagnosis

A psychiatrist is a medical professional with expertise in the diagnosis and treatment of mental health issues. Psychotherapists and other mental health providers, such as psychologists, are qualified to diagnose anxiety and offer psychotherapy.

The mental health professional do the following to assist in the diagnosis of an anxiety disorder:

- Provide a psychological assessment.

  This entails talking about your feelings, ideas, and actions in order to make a diagnosis and look for any associated problems. Diagnosing anxiety disorders might be more difficult since they frequently coexist with other mental health issues like depression or drug abuse.
- Examine your symptoms in relation to the DSM-5 criteria.

  A lot of medical professionals base their diagnosis of anxiety disorders on the criteria included in the American Psychiatric Association's Diagnostic and Statistical Manual of Mental Disorders (DSM-5).

1.7.2 Treatment

Pharmacological therapy and psychotherapy are the two primary therapies for anxiety disorders. The combination of the two is most beneficial to the patients. Finding the optimal remedies may need some trial and error.

- Psychotherapy

  Working with a therapist to reduce your anxiety is known as psychotherapy, sometimes known as talk therapy or psychological counseling. It could be effective as treatment for anxiety. Cognitive behavioral therapy (CBT) is the most effective kind of psychotherapy for anxiety problems. Often a short-term treatment, cognitive behavioral therapy (CBT) gives a specific techniques to assist control your symptoms and gradually resume the activities that has been avoided because of anxiety.

  As part of CBT, the person will gradually be exposed to the situation or object that causes you anxiety so that he/she may become more confident in his/her ability to manage it.

- Medications

  Depending on the kind of anxiety illness you have and whether you also have other physical or mental health conditions, several drugs can be used to aid with symptoms. As an illustration: Anxiety problems are also treated with several antidepressants. One possible prescription is for buspirone, an anti-anxiety drug. In certain situations, doctor could recommend different kinds of drugs, such beta blockers or sedatives, which are also known as benzodiazepines. These drugs are not meant to be used long-term; they are meant to provide temporary relief from anxiety symptoms.

1.8 EEG - ELECTROENCEPHALOGRAM

Various investigations have been carried out to ascertain the electrophysiological and electroencephalographic association of anticipatory anxiety caused in individuals. There are several ways to record data on the composition and operations of the brain. Electroencephalography (EEG), magnetoencephalography (MEG), and magnetic resonance imaging (MRI) are the three widely utilized modalities. When it comes to analyzing brain activity, EEG is the most practical and economical approach. It may be used to create a large-scale connectivity model of brain processes as well as to examine the neurological correlates of social anxiety [27].

An EEG is a test that looks for anomalies in your brain's electrical activity, or brain waves. Electrodes are applied to your scalp during an EEG. These are tiny metal disks connected by slender wires. They pick up microscopic electrical charges produced by your brain's cell activity. On a computer screen, the charges are magnified and display as a graph. Alternatively, the recording might be printed on paper.

The purpose of this project, 'Detection of Anxiety Disorder using EEG signals' is to:

Establish context: Understand the existing knowledge and research in the field of EEG signal processing and anxiety disorder detection.

Identify gaps: Identify gaps or areas where current research lacks solutions or where improvements can be made.

Inform methodology: Using existing studies to inform the methodology in my project, helps in deciding the most appropriate approaches and techniques.

Support hypothesis: It provide evidence to support hypothesis or research question.

Gain insights: Gain insights into the challenges, trends, and best practices in EEG signal processing for anxiety disorder detection.

Generate ideas: Generate new ideas or directions for my research based on the findings and gaps identified in the literature.

CHAPTER 2: LITERATURE SURVEY

2.1 RELATED STUDIES

Anxiety disorders are a prevalent mental health issue, affecting a significant portion of the global population. The use of EEG signals for the detection of anxiety disorders has gained attention in recent research. Machine learning methods have been applied to EEG signals to analyze the brain functions and attentional bias associated with anxiety disorders. These studies have shown that EEG signals can provide valuable insights into the underlying neural mechanisms of anxiety and may serve as potential biomarkers for early detection and diagnosis of anxiety disorders. Furthermore, studies have explored the use of group structure information and nonlinear correlation analysis to improve the accuracy of anxiety disorder detection using EEG signals. By dividing EEG signals into different brain regions and visual behaviors, researchers have been able to capture the complex nonlinear relationships between EEG and eye movement features. This approach has shown promise in enhancing the understanding of anxiety disorders and improving the accuracy of their detection. (Guo et al., 2020)

Additionally, the use of kernel group sparse canonical correlation analysis has been proposed as a method to study the nonlinear complex relationship and group structure information among EEG and eye movement features. This approach involves transforming the data into kernel space using a Gaussian kernel function, which effectively generates a nonlinear cooperative fusion representation. This method allows for a more comprehensive analysis of the relationship between EEG and eye movement signals in the context of anxiety disorders. Overall, the literature review indicates that EEG signals hold great potential for the detection of anxiety disorders. Moreover, the use of machine learning algorithms, such as SVM, Naïve Bayes, Decision tree, and KNN, has been explored in(Guo et al., 2020) order to improve the accuracy of anxiety disorder detection using EEG signals. These algorithms have shown promising results, achieving high classification accuracy rates ranging from 87.47\% to 98\%. Furthermore, there is increasing recognition of the importance of EEG signals in the diagnosis and treatment of sleep disorders. The use of EEG signals, along with other biomedical signals like electrooculography, in the classification and diagnosis of sleep stages has shown promising results.

The connection between mental states and brain activity is demonstrated by the electrical activity of the brain captured on an electroencephalograph (EEG), which offers extensive details on the processes of the central nervous system [20]. Consequently, the focus of researchers has shifted to using an EEG to identify a person's mental state (emotions, worry, tension). for example in [1] These authors offer a novel method of diagnosing social anxiety disorder, which has significant ramifications for both individuals and society. The purpose of the study is to use machine learning methods and the fuzzy entropy measure to examine the EEG complexity of participants who are classified into four groups: severe, moderate, mild, and healthy controls. The resting-state FE value was favorably connected with the fast waves (alpha and beta) Social Interaction Anxiety Scale (SIAS) scores. With an accuracy of 86.93\%, sensitivity of 92.46\%, and specificity of 95.32\%, the Naive Bayes (NB) classifier is employed.

In [2] A deep convolutional neural network (CNN), long short-term memory (LSTM), and directed causal impacts are used by the author to build an electroencephalography (EEG)-based detection model for SAD. The EC characteristics, which come from the cortical correlation within various EEG cycles for certain cortical regions that are more prone to SAD, are used as input by the DL model. In order to distinguish between the severity of SAD (severe, moderate, and mild) and healthy controls (HC) at various frequency bands (delta, theta, alpha, low beta, and high beta) in the default mode network

(DMN) under resting-state conditions, the EEG data were classified using three different DL models: CNN, LSTM, and CNN+LSTM. The suggested model (CNN+LSTM) performs better than the other models in SAD recognition, according to experimental findings. The CNN+LSTM model produced the best recognition accuracies (92.86\%, 92.86\%, 96.43\%, and 89.29\%), specificities (95.24\%, 95.24\%, 100\%, and 90.91\%), and sensitivities (85.71\%, 85.71\%, 87.50\%, and 83.33\%) for the severe, moderate, mild, and HC categories for our dataset.

In [3] Using the standard gelotophobia rating instrument (GELOPH<15>) and the structured clinical interview for the Diagnostic and Statistical Manual of Mental Disorders (4th edition), the author examines the connection between gelotophobia, SAD, and avoidant personality disorder (APD). When compared to healthy controls and other psychiatric patients, individuals with SAD and APD had considerably higher ratings for phobias. In [4] In order to comprehend the significance of a collection of biomarkers with four different forms of anxiety disorders—Generalized Anxiety Disorder (GAD), Agoraphobia (AP), Social Anxiety Disorder (SAD), and Panic Disorder (PD)—the author used machine learning techniques. retrieved the factors that were important in causing a certain kind of anxiety condition using a variety of machine learning algorithms. 28 biomarkers were retrieved from the Dutch Lifeline biobank using data from that biobank. Red blood cell count, immune system cell count, and biomarkers suggesting kidney and liver function were the four groups into which biomarkers were divided. Supervised machine learning with binary classification was employed by the writer. it consider two main approaches i.e the Univariate and multivariate approach to understand the importance of model based biomarkers. The result shows common biomarker features from all the four biomarker clusters.

In [5] The Preschool Age Psychiatric Assessment (PAPA) data from the two large community studies was already collected, so the study used machine learning tools to identify subsets of PAPA items that could be developed into a valid, efficient, and effective screening tool to determine a young child's risk for anxiety disorders. With an accuracy of over 96\% for both separation anxiety disorder (SAD) and generalized anxiety disorder (GAD), they were able to reduce the number of elements required to identify a kid who is at risk for an anxiety disorder by an order of magnitude using machine learning. Additionally, they give a continuous risk score that indicates the child's likelihood of fulfilling the criteria for either SAD or GAD rather than treating them as discrete or binary entities. Authors compared 15 different machine learning algorithm in the context of the diagnosis of autism, showing that ADTrees approach is the best possible machine learning algorithm. They used 5 nodes for the GAD model.

In [6] focuses on providing a comprehensive literature review on the application of machine learning algorithms for anxiety disorder such as Generalized anxiety disorder, Panic Disorder, Social mental disturbance and post traumatic disturbance. The primary goal of this work is to present a thorough overview of the literature on the use of machine learning algorithms for the diagnosis of anxiety disorders, the assessment of treatment outcomes, and the prediction of anxiety disorder began. Medical professionals have shown a number of benefits from clinical decision support systems based on data-driven classifier design. The last ten years have seen a surge in social media use, and wearable sensor technology has created new avenues for the discovery of more effective clinical decision support. However, there is still much space for improvement in terms of diagnostic quality, and novel treatment approaches may be employed to improve overall population mental health and lessen the likelihood that mental illness would result in grave consequences like suicide. Understanding the population's levels of anxiety, sadness, and mood can also aid in improved government decision-making.

In these papers [7], the author investigates college students' test anxiety and stress awareness when they are enrolled in scientific courses and taking exams. real-time anxiety awareness during scientific tests in a classroom setting, as enabled by biofeedback. The primary questions to investigate are how students' anxiety affects their performance and how their knowledge of their anxiety affects their mindset in regard to academic success, as shown by biofeedback. According to pertinent research, there is a strong correlation between pupils' performance and their anxiety level.

An algorithm that can analyze complicated data with a heterogeneous distribution is referred to as machine learning [25]. Without requiring human input, machine learning algorithms offer automated solutions for decision-making. Many industries, including education, economics, clinical decision support systems, and medical imaging, have used this technology [26].

This study [8] proposed a machine learning (ML) method to perform such predictions for Selective Serotonin Reuptake Inhibitor (SSRIs) using pre-treatment EEG data. To accomplish this, experimental data from 34 MDD patients and 30 healthy controls were acquired. Consequently, a feature matrix was constructed using time-frequency decomposition of EEG data based on wavelet transform (WT) analysis, which is called the EEG data matrix. The resultant EEG data matrix had a high dimensionality, so dimension reduction was carried out using a rank-based feature selection method according to a criterion, i.e., receiver operating characteristic (ROC). As a result, the most significant features were identified and further used during the training and testing of a classification model. Ten-fold cross-validation (10-CV) was used 100 times to validate the LR model. Empirical mode decomposition (EMD) and short-time Fourier transform (STFT) analysis were used to compare the categorization findings. It was discovered that the wavelet characteristics taken from the temporal and frontal EEG data were statistically significant. With an accuracy of 87.5\%, sensitivity of 95\%, and specificity of 80\%, the WT analysis has demonstrated the greatest classification accuracy when compared to other time-frequency techniques like the STFT and EMD. In conclusion, the treatment result of antidepressants for MDD patients may be predicted by significant wavelet coefficients that were derived from frontal and temporal pre-treatment EEG data including the delta and theta frequency bands.

The effectiveness of the instrumented fear induction task, which the authors propose in [9] to employ to detect children with internalizing disorders, is demonstrated in a group of 63 children aged three to seven. Using data from a belt-worn inertial measuring unit (IMU), they are able to extract objective metrics that capture a kid's entire six degrees of freedom of movement. They then correlate these measures with behavioral fear codes, parent-reported child symptoms, and clinician-rated internalizing diagnoses for children. In this sample, they find that IMU motion data are linked with parent-reported child symptoms and clinician-reported child internalizing diagnoses, but not behavioral codes. These findings show that behaviors suggestive of child psychopathology may be detected in IMU motion data. Furthermore, the suggested technique based on IMUs had made collecting and processing more feasible.

The author used aspects of transiently stable brain states (micro-states) in [10] to evaluate differences in resting state activity between PD patients and normal controls based on EEG. Analysis was done on the EEG's of 18 drug-naive patients and 18 healthy controls. One class of micro-states (with the mapped field oriented from right-anterior to left-posterior) had longer duration and covered a larger percentage of the total time in the patients compared to the controls, according to micro-state analysis. When comparing the patients to the controls, a different micro-state class (with a symmetric, anterior-posterior orientation) was seen less frequently. Certain brain processes may already be changed under resting conditions, as evidenced by the finding that certain micro-state classes differ between PD patients and controls.

This [11] study's data source is the YMM, the second Australian Child and Adolescent Survey of Mental Health and Well being 2013–14. The factors that had a poor association have been removed. To identify the most crucial characteristics for depression identification among the highly correlated variables with the target variable, the Boruta method has been used in conjunction with a Random Forest (RF) classifier. The selection of appropriate supervised learning models has been done using the Tree-based Pipeline Optimization Tool (TPOTclassifier). RF, XGBoost (XGB), Decision Tree (DT), and Gaussian Naive Bayes (GaussianNB) have all been utilized in the depression identification stage. Eleven key indicators of depression in children and adolescents have been identified: unhappy, nothing fun, irritable mood, diminished interest, weight loss or gain, insomnia or hypersomnia, psychomotor agitation or retardation, fatigue, difficulty thinking or concentrating, indecision, or plan to commit suicide. If any of these five symptoms are present, it is considered important to identify the depression. RF beat all other methods in 315 milliseconds (ms) to predict depressed classes by 99\% with a 95\% accuracy rate and a 99\% precision rate, despite considerable variation in model performance.

In [12] this publication, author present an experimental investigation that uses new noise filtering techniques to gather breathing and heartbeat data from 15 subjects based on radio frequency (RF) reflections off the body. A new deep neural network (DNN) architecture that combines processed and raw RF data to categorize and visualize different emotional states. For independent subjects, the suggested model obtains a high classification accuracy of 71.67\% with precision, recall, and F1-score values of 0.71, 0.72, and 0.71, respectively.

In [13] this study author uses physiological signals from electroencephalography (EEG) to build an objective framework for assessing human anxiety that is recorded in response to exposure treatment. To quantify anxiety into two and four levels, twenty-three participants' EEG signals from an already-existing database named "A Database for Anxious States which is based on a Psychological Stimulation (DASPS)" are employed. To eliminate undesired ocular and muscular artifacts, the EEG data are pre-processed using the proper noise filtering techniques. Channel selection is carried out using statistical analytic approaches to identify the substantially distinct electrodes. Specific EEG channel data is collected in the frequency domain to extract features. Theta and beta bands are the EEG frequency bands used in this study. Frequency band selection is used to choose the best combination of these bands. Machine learning techniques were used to classify the chosen selection of characteristics from the relevant frequency bands of the statistically significant EEG channels. A random forest classifier with 9 and 10 characteristics achieves an accuracy of 94.90\% and 92.74\% for the two- and four-level anxiety classification, respectively.

In[14] the goal was to find out whether a group of students with learning impairments that were not otherwise identified belonged to any subgroups and whether their EEG patterns were distinct. Included were 85 participants (31 female, 8–11 years old) who received low scores on at least two of the Infant Neuropsychological Evaluation's subscales: reading, writing, and math. With the eyes closed, electroencephalograms were recorded in 19 leads while at rest; absolute power was measured at intervals of 0.39 Hz. Group 1 (G1, higher scores than Group 2 in reading speed and reading and writing accuracy), Group 2 (G2, better performance than G1 in composition), and Group 3 (G3, lower scores than Groups 1 and 2 in the three subscales) were the three subgroups created based on the children's performance. G3's absolute power in frequencies was greater. Three subgroups were found with different cognitive profiles, as well as a different electroencephalographic pattern.

The author in [15] use a psychophysiological database including 213 subjects—92 depressive patients and 121 normal controls—was created for the current investigation. A three-electrode widespread prefrontal-lobe EEG device (Fp1, Fp2, and Fpz) was used to record the EEG signals of all subjects during resting state and sound stimulation. A total of 270 linear and nonlinear features were retrieved after denoising using the Finite Impulse Response filter, which used the Kalman derivation method, Discrete Wavelet Transformation, and an Adaptive Predictor Filter. The feature space's dimensionality was then decreased using the minimal-redundancy-maximal-relevance feature selection method. The participants who were depressed were separated from the normal controls using four different classification methods: Support Vector Machine, K-Nearest Neighbor, Classification Trees, and Artificial Neural Network. Ten-fold cross-validation was used to assess the classifiers' performance. This study establishes the feasibility of a pervasive three-electrode EEG acquisition system for depression diagnosis. The results also suggested that the absolute power of the theta wave might be a valid characteristic for discriminating depression. K-Nearest Neighbor (KNN) had the highest accuracy of 79.27\%.

This study of [16] suggests a technique that uses deep characteristics and a Takagi-Sugeno-Kang (TSK) fuzzy system to automatically identify college students' anxiety. Preprocess the college students' obtained EEG first. Second, to extract deep features from the input data, employ a convolutional neural network (CNN). In order to determine the final recognition result, features are finally classified using the

TSK fuzzy algorithm. The outcomes of the experiment provide as more proof that depth characteristics are more informative than standard features. The TSK fuzzy system performs well in classification and generalization because to its tolerance to noise. The identification outcomes enable prompt identification of individuals with anxiety disorders and focus the investigation's parameters on pupils exhibiting psychological issues. Teachers and institutions can work more efficiently if they can automatically identify the anxiety that college students experience.

In this research paper [17] the author first investigate, that MA(Mathematical Anxiety) influences the first phases of the WM's(Working Memory) processing of numerical stimuli through the use of event-related potentials in scalp electroencephalogram (EEG) data. This work investigates the cortical activations—obtained by multichannel EEG recordings—as well as the cortical functional networks in three progressively challenging working memory tasks. According to our findings, the low-math anxious (LMA) group activated areas connected to the WM's encoding and retrieval processes, while the high-math anxious (HMA) group engaged more areas associated with negative emotions, pain, and fear. Additionally, according to functional connectivity analysis, the brains of the LMAs and HMAs exhibit more diffused and unstructured networks, respectively, suggesting a corruption of the structured processes of WM. The LMAs' brains have more structured cortical networks with increased connectivity in areas related to WM, such as the frontal cortex.

The scope of the use of deep learning has expanded greatly to different application domain, including the classification of various signals representing emotional stress[18,19]. With the use of massive data sets, this type of method may identify the most unique characteristics. Thus, in the area of mental state identification, comparable techniques are being applied more and more often to EEG data analysis.

Jebelli [21] demonstrated the efficacy of this strategy in a later work. A fully connected deep neural network (FC-DNN) and a convolutional deep learning neural network (CNN) were the two deep learning architectures that the authors examined. The greatest accuracy achieved by the best-configured DNN in identifying workers' stress was 86.62\%. When compared to their prior manual feature-based techniques, it was at least six percentage points more accurate [20].

EEG based detection technique that makes use of geographical data is used in [24] to classify depression. Thirty participants—sixteen of whom were patients with depression and fourteen of whom were healthy controls—were given a face-in-the-crowd test that included both positive and negative emotional facial expressions. For feature extraction and selection, the evolutionary algorithm and differential entropy were employed, while a support vector machine was utilized for classification. Before feature extraction, a task-related common spatial pattern (TCSP) was suggested to improve the spatial disparities. Using TCSP, the cross-validation classification result was 84\% and 85.7\% for positive and negative stimuli, respectively. The gamma band made up the majority of the contribution when we used individual frequency bands to assess the categorization performance. Several classifiers, such as logistic regression and k-nearest neighbor, which demonstrated comparable patterns in the enhancement of classification with the use of TCSP.

Four distinct stress levels—relaxed, absorbed, stressed, and anxious—are identified by an algorithm presented by Hou et al. [23] in response to the Stroop Color and Word Test (SCWT). Combining statistical characteristics with fractal dimension and utilizing SVM as the classifier yielded results of 67.06\%. Another source of stress was the SCWT [22]. Using an EMOTIV EPOC wireless device, the scientists created an automated EEG-based stress identification system. Three degrees of stress were identified with a 75\% accuracy rate by using the relative difference of beta and alpha power as a feature and SVM as a classifier. With rapidly increasing interest in the EEG signal processing, deep learning based classification method gained significant attention in the previous work. The method such as Support Vector Machine (SVM) and Convolutional Neural Network (CNN) presented improved performance accuracy for EEG signals of anxiety disorder.

2.2 LITERATURE SURVEY CONCLUSION

The insights from some of the research papers are about the EEG based detection technique that makes use of the data to classify different problems related to brain. It highlights the main aspects, like how EEG data is being helpful for identifying the disorder in the human brain which can be helpful for the patients for their early treatment. Different authors worked in different areas of the brain with different approaches. Different stimuli are used by the authors for eg. showing videos and image, blinking of the eye test etc. First is to find how many electrodes we are using in our study as there are multiple electrodes caps of EEG system are available. The 10- 20 system EEG head cap having 32 electrodes (FP1, FP2, FPz, F7, F8, F3, F4, FC5, FC1, FC2, FC6, Fz, Cz, T8, P7, P8, C3, C4, C3, CP2, CP4, CP1, CP6, CP5, P3, P4, PZ, O1, O2, and POz) to collect the data. The signals generated are too noisy, different pre-processing technique are used to get good result. After pre-processing of the data next step is to classify the data and analyze the results. There are various machine learning algorithms and classification methods are used by the authors. A brief summary describing the earlier finding on anxiety disorder using EEG signals and the related work is presented in the below table.

Sr. No	Authors	Purpose	Stimuli	EEG Dataset	Algorithm/Features	Performance Matrix		
01	Jennifer. L Hudson,	Informing early intervention:	• Resting	Subject: 102 (behaviourally)	• Short Temperament		B1	B2
	Helen F. Dodd	Preschool Predictors of Anxiety	• Motor	In habited 7 100(BUI)	• Scale for children (STSC)	Anxiety Disorder	68%	18%
	(2012)	Disorders in Middle Childhood	• Behaviour of	Age:4Years	• Multi-method design	Social Phobia	42%	-
			• Child/subject	• University: - Macquarie	• Anxiety Disorders Interview	Separation AD	34%	2%
		• Same sex unfamiliar	• Response to new	University, Sydney, New	• Schedule (ADIS-P-IV)	Specific Phobia	45%	12%
		Peer was observed	Room, novel toy,	South Wales, Australia	• Parent Protection Scale (PPS)	GAD	8%	3%
			Masked experimenter		• Five-minute speech	Obsessive Compulsive	1%	2%
			Dressed in stranger suit		Sample (FMSS)	Disorder		
02	Havranek MM,	The Fear of being laughed at as	• Resting	Psychiatric Diagnoses	• Structured clinical interviewer	(GELOPH <15>) were		
	Volkart F,	Additional diagnostic criterion	• Questionnaires	Subject: - 133	For DSM-IV (SCID-I)	Higher in patient		
	Bolliger B, Rooss,	In social anxiety disorder and		(64 psychiatric + 69 healthy)	• Structured Clinical Interview	Compared to contract		
	Buschner M,	Avoidant		Aged:19-32 Years	For DSM-IV Axis II	GELOPH <15>		
	Mansour R et al.			University: - University of	(SCID)	Scores higher than		
	(2017)			Zurich	• GELOPH <15>	2.5		
03	Brailovskia J.	Facebook Addiction Disorder	• Resting	Subject: - 300	• Satisfaction with life scale	• FAD fully mediated the		
	Margraf	(FAD) among students-	• Questionnaires	Age (22-52)	(SWLS)	Significant positive		
	(2017)	A longitudinal approach		S1 Dataset	• Questionnaire Social Support	Relationship between		
				• Online Survey	(F-SOZ UK-14)	Narcissism and stress		

				• University:- Ruhr-	• Depression Anxiety	symptom
				• Universitat Bochum	Stress scale 21	• Narcissistic people are risk to
				• German	(DASS-21)	Develop FAD
					• Bergen Facebook	
					Addiction Scale (BFAS)	
					• Narcissistic Personality	
					Inventory (NPI-13)	

SR.NO	AUTHORS	PURPOPE		DATASET	ALGORITHMS/ FEATURES	PERFORMANCE
04	Sharma A, Verbeke	Understanding importance of clinical		Subject: - 11,081	• ML Algorithms	• The biomarkers within All four
	WJMI (2021)	biomarkers for Diagnosis of anxiety disorders		Software: - IBM,	• Generalised Linear	clusters of biomarkers were
		using machine Learning models		SPSS and R	Model (GLM)	Commonly associated with the
			Stimuli	Programming	• Random Forest (RF)	Four anxiety disorder
			Questionnaires		• Support Vector Machine (SVM)	(i.e. GAD, AP, PD and SAD)
					• Gradient boosting	
					• Model (GBM)	
					• Neural Networks (NN)	
05	Carpenter KLH,	Quantifying risk for anxiety disorder in		Subject: 3433	- The Preschool age Psychiatric	The algorithm provides a very
	Sprechmann P,	Preschool children: A Machine Learning		Children	Assessment (PAPA)	Reliable risk estimator with
	Calderbank R,	Approach		Age: - 2 to 5 Years	Test Retest	Accuracy values of 97% and 99%
	Sapiro G, Egger HL.		Stimuli	University:- Duke University	Study (PTRTS)	For GAD AND SAD respectively.
	(2016)		Questionnaires	School of Medicine,	- The Duke Preschool	
				Durham North Carolina,	Anxiety study (PAS)	
				United States of America	- Alternating decision trees	
					Algorithms (AD trees)	
06	Muhammad Arif,	Classification of anxiety disorders using			- Machine Learning Algorithm	GAD-99%
	Basri A, Melibari	Machine learning methods:				ST-93%
	G,et al.	A Literature review				PD-79%
	(2020)			Subject : 1000	- To predict the outcome	SAD-89%

	i. Kessler et al				PTSD-82%
			Subject : 68+33	- Integrated clinical and Imaging	Pediatric-80%
	ii. Meenal, et al			Feature	
			Subject : 740	- Logistic regression, Naïve	
	iii. Sau, et al			Bayes, Random Forest, and	
				Suppor Vector Machine	
				And cat boost	

SR.NO	AUTHORS	PURPOSE	STIMULI	EEG DATASET	ALGORITHM/FEATURES	PERMFORMANCE
07	Kikuchi M, Koenig T, Munesue T, Hanaoka A, Strik W, et at. (2011)	EEG Microstate Analysis in Drug-Naïve Patients with panic disorder	Resting Eye Open Eye Closed Condition	- Channel-18 - Subject-18 - (11 M & 7W - Kanazawa University Hospital, Japan	- K-Mean Clustering Algorithm - Permutation Algorithm	Patients with PD show Alterations in a specific Subset of brain.
08	Mumtaz W, Xia L, Mohd Yasin MA, Azhar Ali SS, Malik AS (2017)	A wavelet-based technique to predict Treatment outcome for major Depressive disorder	Resting - Eye Closed and Eye Open condition - Visual oddball task - Random sequence of Shapes are shown on screen	• Channel-19 • Subject-64 (34-MDD & 30 Healthy) • Age=40.3 ±12.6 • Hospital Universiti Sains Malaysia (HUSM)	• Time Frequency Decomposition • Logistic regression (LR) • (STFT)-Short Term Fourier transform Analysis	• Accuracy- 87.5% • Sensitivity -95% • Specifically-80%
09	Roca Stappung M, Fernandez T, Bosch Bayard J, Harmony T, Ricardo - Garcell J. (2017)	Electroencephalographic Characterization of subgroups of Children with learning disorders	Resting • Eyes Open • Eye Closed • Condition • Reading, Writing and Arithmetic	• Channel-19 • Subject-85 (3) F & 54M) • Age-Between 8 and 11 Years • University: - National Autonomous University of Maxico	• ANOVA Test Wechsler Intelligence Scale for children-IV (WISC-IV)	3 sub-group have different Cognitive profile with differences In the EEG spectral profile.
10	Carpenter KLH,	Quantifying risk for anxiety disorders	Resting	• Subject-B433	• Preschool Age	ML derived screening trees could

	Sprechmann P,	In preschool children: A Machine	Questionnaires	• Age-2 to 5years	• Psychiatric Assessment	Be used to create valuable
	Calderbank R,	Learning Approach.		Duke University	(PAPA) Test	Tools for screening young children
	Sapiro G,			Paediatric Primary	• Preschool Anxiety	With impairing SAD and GAD
	Egger HL			Care clinic USA	• Study (PAS)	
	(2016)				• Alternating decision	
					Trees algorithm	
					(AD trees)	

SR.NO	AUTHORS	PURPOSE	STIMULI	EEG DATASET	ALGORITHM/FEATURES	PERMFORMANCE
11	Del Popolo Cristaldi F,	Dealing with uncertainty A high.	• Resting	• Subject: - 36 Male	• S1-S2 Paradigm	The slopes of IUS trend for each
	Mento G, Sarlo M,	Density EEG investigation on how	24 coloured emotional	• Age: 23-25	• Processing-MATLAB	Level of factors were estimated
	Bluodo G	Intolerance of uncertainty affects	Faces	• University of Padova	Toolbox EEGLAB	And pairwise difference tested.
	(2021)	Emotional predictions	• Reading the on screen	• Elastic 128-ch EEG	• 14.1.2b	
			task	net	• Interpolation Method	
					• TBT algorithm	
					• The infomax algorithm	
					• ERP's statistical	
					Analysis	
					• Permutation approach	
12	Mumtaz W, Xia L,	A wavelet-based techniques to	• Resting	• Subject: - 34 MDD	• Beck Depression	• Accuracy=37.5%
	Mohd Yasin MA,	Predict treatment outcome for major	• Eye Closed	(17M and 17F)	Inventory Ⅱ (BDI) Ⅱ	
	Azhar Ali SS, Malik AS	Depressive disorder	• Eye Open	• Age=40.3±12.9	• Hospital Anxiety and	• Sensitivity=95%
	(2017)		• Visual-Shapes were	• EEG (19) ch	Depression scale (HADS)	
			Displayed on the	• Hospital Universiti	• Wavelet transform	• Specifically=30%
			Computer screen	Sains Malaysia	Analysis (WT)	
				(HUSM), Kelantan	• Short-Time Fourier	
				Malaysia	Transform (STFT) analysis	
					• Empirical mode	
					Decomposition (EMD)	
13	Muhammad F, AL-					
	Ahmadi S.	Human state anxiety classification	Resting	Subject;23	• Hamitton Anxiety Rating	• Accuracy 94%
	(2022)	Framework using EEG signals in	• Auditory events	(10M and 13F)	Scale (HAM-A)	And 92.74%
		Response to exposure therapy		• Emotiv EPOC EEG	• Self-Assessment Manikin	For two & four level

				Wireless headset	(SAM) Scale	Anxiety classification
				• 14ch	• Blind source separation	
				• EEG Lab	Canonical correlation	
				• College of Computer	Analysis-based algorithms	
				And Information	• Improved Weighted	
				Sciences, King Saud	Adjusted second-order	
				University Riyadh,	Blind identification method	
				Saudi Arabia	(IWASOBI)	
					• Welch algorithm	
					• Fast Fourier Transform	
					(FFT)	

SR.NO	AUTHORS	PURPOSE	STIMULI	EEG DATASET	ALGORITHM/FEATURES	PERMFORMANCE
14	Boehme S, Ritler V. Tefikow S, Stangier U, Strauss B, Miltner WHR et al (2015)	Neural correlates of emotional Interference in social anxiety disorder	• Resting • Showing words and Participant are Requested to name Ink colour of the word As fast as possible	• Subject: 33 17 with SAD and 16 Healthy, • Software-SPSS (Version 18.0.2 • Software package brain Voyage QX Software • Matlab (Version 7.8) • University of Jena Germany	• Structured clinical Interview for DSM-Ⅳ Axis Ⅰ & Ⅱ disorders • Liebowitz social anxiety Scale (LSAS) • Beck Depression Inventory (BDI) • Functional Magnetic Resonance imaging (FMRI) • SAM-Self Assessment	Analysed reaction time Differences in response to Social VS Neutral stimuli
15	Hanshu Cai, Jiashuo Han, Yuntie Chen, Xiaocong Sha, Ziyang Wang, Bin Hu, Jing Yang, Lei Feng, Zhijie Ding, Yiqiang Chen, and Jürg Gutkencht (2013)	A pervasive approach to EEG-based Depression detection	• Resting • Little body movement • Different sound track • Eyes Closed	• Subject:213 (92 depressed Patients and 121 Normal patients) • Pervasive 3-electrode EEG acquisition System • Software: MATLAB (Version R2014a)	• MMSE Questionnaire • Patient Health Questionnaire (PHQ-9) • Life Event Scale (LES) • Pittsburgh Sleep Quality Index (PSQI) • Generalized Anxiety Disorder (GAD) Scale. • Kalman Filter Algorithm • Discrete Wavelet Transformation (DWT) • Adaptive Predictor Filter (APF)	K-Nearest Neighbour (KNN) Had the highest accuracy of 79.27%

					• Adaptive Auto Regressive	
					(AAR) Model	
					• 4-Classification Algorithms	
					i) K-Nearest Neighbor (KNN)	
					ii) Support Vector Machine	
					(SVM)	
					iii) Classification Tree (CT)	
					iv) Artificial Neural Network	
					(ANN)	

SR.NO	AUTHORS	PURPOSE	STIMULI	EEG DATASET	ALGORITHM/FEATURES	PERMFORMANCE
16	Haque UM,	Detection of child depression using	• Resting	• Subject-6310	• Boruta algorithm	95% accuracy
	Kabir E, Khanam R.	Machine learning methods		• Age-4-17Years	• Tree based pipeline	
	(2021)				Optimization tool	
					(TPOT Classifier)	
					• RF algorithm	
17	Choi JY, Lee JH, Choi Y,	Prediction of disorders with	• Resting	• Subject-3382	• Philips 12-Lead algorithm	In multivariable analysis, AUC
	Hyon Y, Kim YH (2022)	Significant coronary lesions using	• Little movement	• Characteristics of	• Fisher's exact test	And accuracy of the model
		Machine learning in patients		Chest pain and	• Mann-Whitney U-test	0.795 and 72.62%
		Admitted with chest symptoms.		Dyspnoea	• CLR was used	
				• Physical Examination	• KNN imputation	
				• Demographics	• LR, support vector machine	
				• Heart Score	(SVM)	
				• University: A and	• Random Forest	
				Samsung Changwon	• Extreme Gradient Boosting	
				University Hospital.	(XG Boost)	
18	Apostolidis H,	Exploring anxiety awareness during	• Test	• Subject:40	• State-Trait Anxiety Inventory	• Post-activity
	Tsistsos T	Academic science examinations	• Multiple Choice	(16M and 24F)	(STAI)	Anxiety students
	(2021)		Test	Age: M=26.31 Year	• Pasco Hernando Community	Experienced regarding
				• Biofeedback device	College (PHCC) text anxiety	The examinations was
				• Neurosky device	Questionnaire.	Lower than their pre-
				• University:-	• General – Self Efficacy (GSE)	Activity anxiety (SUM).
				Aristotle University	Scale	
				of Thessaloniki,	• Number facility test (NF)	

				Greece		

SR.NO	AUTHORS	PURPOSE	STIMULI	EEG DATASET	ALGORITHM/FEATURES	PERMFORMANCE
19	MC Ginnis EW, McGinnis RS, Hruschak J, Bilek E, Ipk, Morlen D, et al 2018	Wearable sensors detect childhood Internalizing disorders during mood Induction task	• Movement • Snake Task in dimly Lit room • Can touch the snake	• Subject: 63 Children • Age: Below 8 Years • Instrument: - Inertial Measurement Unit (IMU) • Behavioural Codes	• Diagnostic Interview and Questionnaires • Snake Tasla • Child Behavior • Checklist (CBCL)	No correlation between Modalities during potential Treat phase.
20	Carpenter KLH, Sprechmann FP, Calderbank R, Sapiro G, Egger HL (2016)	Quantifying Risk for anxiety Disorders in preschool children: A Machine Learning Approach	• Questionnaires used to screen Parents of the Subject.	• Subject:1073 Children • Age: 2-5 Years • University:- Electrical and Computer Science, Duke University USA	• Preschool Age • Psychiatric Assessment (PAPA) • 99 item CBCL 1.5-5 • Strength and Difficulties Questionnaire (SDQ) • A Herniating decision trees Algorithm (AD trees) • Preschool Anxiety Study (PAS) • J48 Algorithm	Accuracy Values of 97% And 99% for GAD and SAD
21	Haque UM, Kabir E, Khanam R (2021)	Detection of child depression using Machine learning methods	• Resting • Questionnaires is used	• Subject: 6310 (5839 non depressed and 471 depressed) Age: 4-17 Years • University of Western Australia	• Boruta algorithm • RF algorithm, TPOT classifier XGB, DT, Gaussian NB.	RF outperformed in Predicting depressed classed By 90% with 95% accuracy And 99% precision

				• Software-Python 3.7.3		
22	Ahsan Noor Khan	Deep learning framework for	• Resting	• Subject:15	• ML Algorithms	Accuracy of 71.67%
	Achintha Avin Ihalage	Subject independent emotion	• Watching videos	• Heart rate	• Radio Frequency Reflection	
	Yihan Ma, Baiyang	Detection using wireless signals	on the monitor	• Respiration rate	• CNN	
	Lui, Yujie Liu, Yang Hao		• Listening music	• EEG	• LSTM	
	(2020)			• University:-	• CW Transformation	
				Queen Mary University		
				of London, United		
				Kingdom		

CHAPTER 3: MATERIALS

3.1 THE PROPOSED ANXIETY DETECTION FRAMEWORK

The project's primary workflow will involve gathering data, pre-processing it, using different approaches for extracting features, and classifying it. The details of each block is explain in the following sub-sections. The structures of proposed anxiety recognition approaches are presented in Figure 1. All steps of the pipelines are presented in details in the following sections.

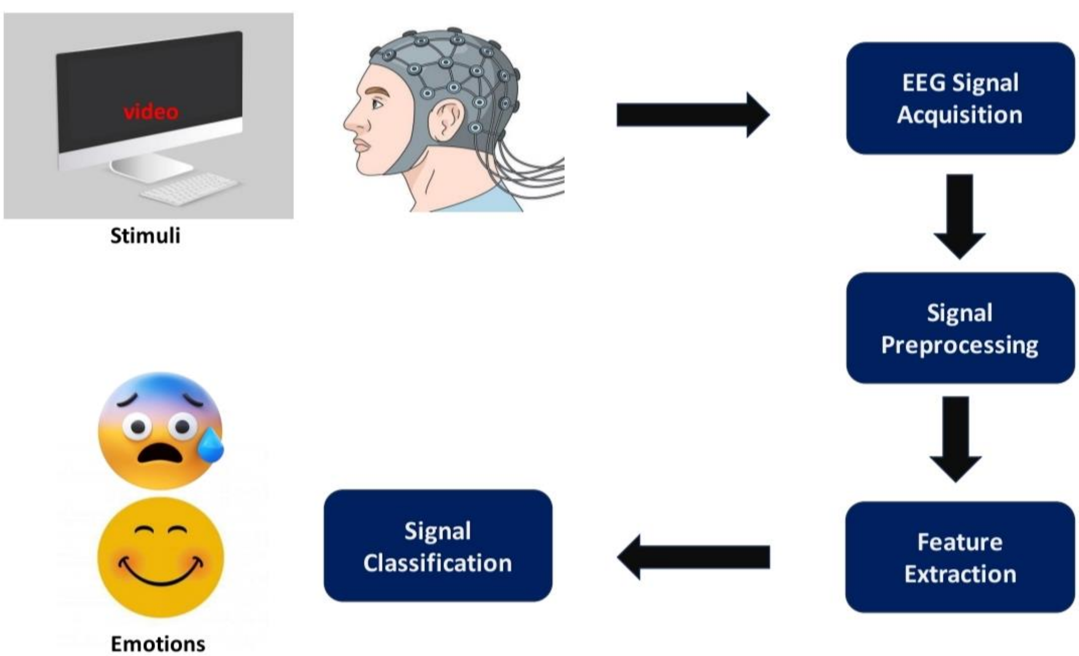

Fig 3.1: Block diagram of Anxiety Detection Framework using EEG head cap.

3.2 EXPERIMENTAL FRAMEWORK

People with phobias and anxiety problems are often helped by exposure treatment, a type of behavioral therapy. It entails a person confronting their fears, whether they be genuine or imagined. It has been proven to be useful and suitable for all age groups. In exposure treatment, a patient is exposed to an incident, circumstance, or thing that makes them feel afraid, anxious, or panicked. Controlled exposure to a trigger by a reliable person in a secure environment can gradually reduce fear or anxiety.

Different types of exposure therapy exist. They may consist of:

- In vivo exposure: In this type of treatment, the feared event or action is faced head-on in the actual world.
- Exposure in the imagination: It entails picturing the trigger scenario in great detail.
- Exposure to virtual reality: When in vivo exposure isn't practical, such as when a person has a phobia of flying, this therapy can be employed.
- Exposure through interception: In this type of therapy, a fearful but innocuous bodily experience is deliberately induced.

3.3 PARTICIPANTS

In this study the data consisting of EEG signals of 42 participants are recorded in the response to virtual reality exposure therapy. EEG signals of 22 healthy participants (7 males, 15 females) and 20 participants (1 male, 19 females) with anxiety disorder having an age between 20 to 50 years of data were recorded during the experiment. The involvement of the participant was entirely voluntary. A written consent was obtained from each participant prior to the start of the experiment. Subjects were informed about their right to stop the study and withdraw their consent at any moment.

3.3.1 Screening of the Participants

The participants were selected based on the following inclusion criteria:

(1) they had no neurological or mental disorders,

(2) they were using VR before and did not report VR sickness symptoms, and

(3) they had normal or corrected (contact lenses) vision and no color blindness.

All participants were informed about the purpose of the study and the procedure of the experiment was explained to them step by step. They authorized informed consent in writing. All participants performed the tests in a quiet and well lit environment with room temperature 22-25° C.

Further participants are screened using GAD-7 test. The General Anxiety Disorder 7-item scale (GAD-7) is one of the tools used to screen for anxiety or to measure its severity. In this test the participants were asked to fill the GAD-7 test questionnaire and scores are measured. on the bases of the score of GAD-7 test, they are classified as a healthy and person with anxiety.

In GAD-7 test there are 7 questions with four options (Not at all, Several days, More than half the days and Nearly everyday). These options are scored as 0, 1, 2, and 3, respectively. They are asked to then tick the box which corresponds most closely to their experience. A total score for the measure can be obtained by adding the totals for each column at the foot of each and adding these together in the Total Score T space shown above. This will give a figure of somewhere between 0 – 21. The increasing scores represent higher levels of symptom severity. In terms of severity the following bands are commonly used:

- 0-5: Mild anxiety
- 6-10: Moderate anxiety
- 11-15: Moderately severe anxiety

- 15-21: Severe anxiety

According to the paper by Spitzer et al [31] a score of 10 or greater on the GAD-7 represents a reasonable cut point for identifying cases of GAD.

	Over the last 2 weeks, how often have you been bothered by the following problems?	Not at all	Several Days	More than half the days	Nearly every day
1	Feeling nervous, anxious, or on edge	0	1	2	3
2	Not being able to stop or control worrying	0	1	2	3
3	Worrying too much about different things	0	1	2	3
4	Trouble relaxing	0	1	2	3
5	Being so restless that it is hard to sit still	0	1	2	3
6	Becoming easily annoyed or irritable	0	1	2	3
7	Feeling afraid, as if something awful might happen	0	1	2	3
	TOTAL SCORE (add the marked numbers):				

The GAD-7 was developed by Drs. Robert L. Spitzer, Janet B. W. Williams, Kurt Kroenke, and colleagues, with an education grant from Pfizer, Inc.

Fig 3.2: GAD – 7 Assessment Test

3.4 ELECTROENCEPHALOGRAM (EEG)

3.4.1 Background on EEG wave analysis

An electrogram of the brain's spontaneous electrical activity can be recorded using electroencephalography (EEG). It has been demonstrated that the postsynaptic potentials of pyramidal neurons in the neocortex and allocortex are represented by the bio-signals picked up by EEG [34]. The International 10–20 system, or variants on it, is usually used to implant the EEG electrodes along the scalp (sometimes referred to as "scalp EEG"). This procedure is usually non-invasive. "Intracranial EEG" is another term for electrocorticography, which involves surgically implanting electrodes in the brain. Visual assessment of the trace or quantitative EEG analysis are the most common methods used for clinical interpretation of EEG recordings.

The EEG bio-amplifier and electrodes monitor voltage fluctuations, which enable the assessment of typical brain activity. Since the neurons in the underlying brain tissue are the source of the electrical activity that is monitored by EEG, the direction and distance of the electrodes on the scalp surface affect the recordings that are produced. In addition, intermediate tissues and bones distort the recorded value in a way that is similar to what happens with resistors and capacitors in an electrical circuit. This means that not every neuron will contribute to an EEG signal in the same way, with cortical neurons near the scalp electrodes contributing the majority of an EEG signal's activity. Deep brain regions that are farther from the electrodes will not directly contribute to an EEG; these structures include the brain stem, hippocampus, thalamus, base of the cortical gyrus, and the mesial walls of the main lobes [35].

The observed frequencies fall within the range of 1 to 30 Hz, whereas the amplitudes exhibit variations between 20 and 100 V. There are four categories 48 into which the recorded frequencies are divided: alpha (8–13 Hz), beta (13–30Hz), delta (0.5–4 Hz), and theta (4–7 Hz). When an individual is in a calm wakeful state, alpha waves are often noticeable over the parietal and occipital locations. In addition to other regions, frontal areas exhibit a greater prominence of beta waves during periods of high mental activity. When someone who is calm is instructed to open their eyes, alpha activity decreases and beta activity increases. When theta and delta waves appear during waking, it indicates a malfunctioning brain [35].

3.4.2 Normal activity

It is also necessary to discuss artifacts observed during the recording of EEG signals. These can be classified as biological or technological and have a variety of origins. In the case of biological artifacts, they originate from organs that are electrically active outside of the brain. For instance, muscular tension abnormalities may be seen in nearly all EEG recordings, with frontal and temporal regions exhibiting the greatest levels of these distortions [41]. That is why a closed/open eyes experiment was conducted before to each EEG test. On the other hand, technical artifacts are documented in relation to electrical device operation. The most frequent cause is an electrode's partial skin contact [42]. It was noticeable in those with long or thick hair as well as in how the participants moved.

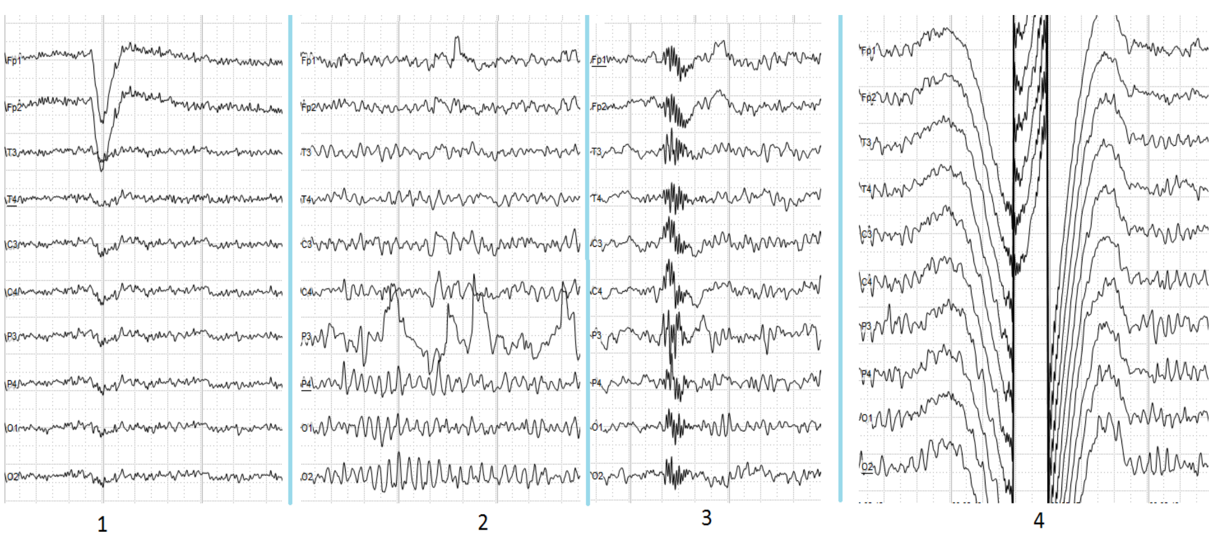

Fig 3.3: Human EEG waves showing artifacts

The above figure shows Common artifacts in human EEG. 1: Electrooculographic artifact caused by the excitation of eyeball's muscles (related to blinking, for example). Big-amplitude, slow, positive wave prominent in frontal electrodes. 2: Electrode's artifact caused by bad contact (and thus bigger impedance) between P3 electrode and skin. 3: Swallowing artifact. 4: Common reference electrode's artifact caused by bad contact between reference electrode and skin. Huge wave similar in all channels.

Generally, two words are used to characterize the EEG: (1) rhythmic activity and (2) transients. By frequency, the rhythmic activity is separated into bands. While these frequency bands are largely a matter of nomenclature (for example, any rhythmic activity between 8 and 12 Hz can be classified as "alpha"), these designations have their roots in the observation that certain frequency ranges of rhythmic activity have particular biological significance or distribution over the scalp. Typically, spectral techniques (like Welch) are used to extract frequency bands. These approaches may be found, for example, in publicly accessible EEG software like EEGLAB or the Neurophysiological Biomarker Toolbox. Quantitative electroencephalography (qEEG) is a common term used to describe the computational processing of the EEG.

3.4.3 Wave Patterns

Delta waves:

Delta wave is the frequency range up to 4 Hz. It tends to be the highest in amplitude and the slowest waves. It is seen normally in adults in slow-wave sleep. It is also seen normally in babies. It may occur focally with subcortical lesions and in general distribution with diffuse lesions, metabolic encephalopathy hydrocephalus or deep midline lesions. It is usually most prominent frontally in adults (e.g. FIRDA –

frontal intermittent rhythmic delta) and posteriorly in children (e.g. OIRDA – occipital intermittent rhythmic delta).

Theta Waves:

Theta is the frequency range from 4 Hz to 7 Hz. Theta is seen normally in young children. It may be seen in drowsiness or arousal in older children and adults; it can also be seen in meditation. Excess theta for age represents abnormal activity. It can be seen as a focal disturbance in focal subcortical lesions; it can be seen in generalized distribution in diffuse disorder or metabolic encephalopathy or deep midline disorders or some instances of hydrocephalus. On the contrary this range has been associated with reports of relaxed, meditative, and creative states.

Alpha Waves:

Alpha is the frequency range from 8 Hz to 12 Hz.[36] Hans Berger named the first rhythmic EEG activity he observed the "alpha wave". This was the "posterior basic rhythm" (also called the "posterior dominant rhythm" or the "posterior alpha rhythm"), seen in the posterior regions of the head on both sides, higher in amplitude on the dominant side. It emerges with closing of the eyes and with relaxation, and attenuates with eye opening or mental exertion. The posterior basic rhythm is actually slower than 8 Hz in young children (therefore technically in the theta range).

In addition to the posterior basic rhythm, there are other normal alpha rhythms such as the mu rhythm (alpha activity in the contralateral sensory and motor cortical areas) that emerges when the hands and arms are idle; and the "third rhythm" (alpha activity in the temporal or frontal lobes).[G][H] Alpha can be abnormal; for example, an EEG that has diffuse alpha occurring in coma and is not responsive to external stimuli is referred to as "alpha coma".

Beta Waves:

Beta is the frequency range from 13 Hz to about 30 Hz. It is seen usually on both sides in symmetrical distribution and is most evident frontally. Beta activity is closely linked to motor behavior and is generally attenuated during active movements [39]. Low-amplitude beta with multiple and varying frequencies is often associated with active, busy or anxious thinking and active concentration. Rhythmic beta with a dominant set of frequencies is associated with various pathologies, such as Dup15q syndrome, and drug effects, especially benzodiazepines. It is the dominant rhythm in patients who are alert or anxious or who have their eyes open.

Gamma Waves:

Gamma is the frequency range approximately 30–100 Hz. Gamma rhythms are thought to represent binding of different populations of neurons together into a network for the purpose of carrying out a certain cognitive or motor function [40].

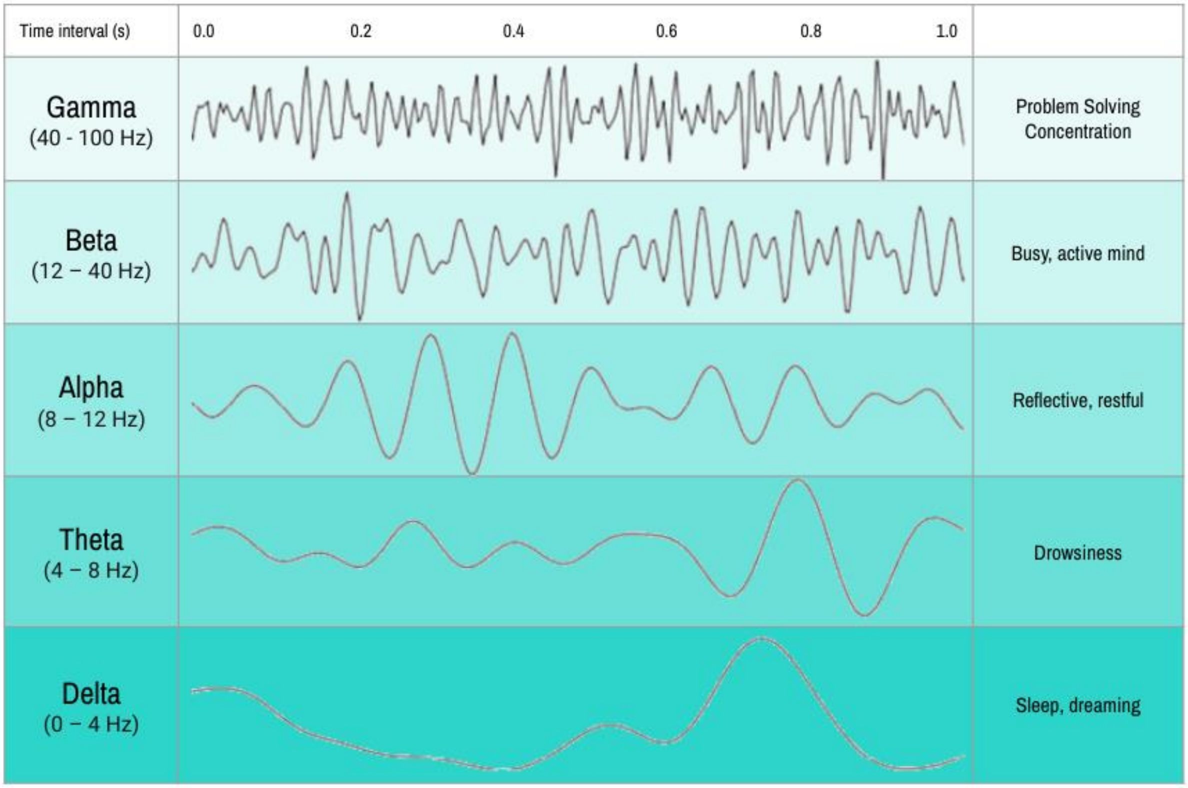

Fig 3.4: Different types of the brain waves

3.4.4 EEG System

An EEG cap R-Net cap from brain products (see Figure 3.5) with 32 channels that was insulated and was used to record the data for the whole 12-minute, 7-second session. These signals were recorded in a closed room away from external disturbances. The EEG signals were acquired using an R-NET1 cap from brain products, consisting of thirty-two passive electrodes along with one ground and a reference electrode, sampled at 250 Hz frequency. The international 10–20 system was used to mount thirty electrodes (FP1, FP2, FPz, F7, F8, F3, F4, FC5, FC1, FC2, FC6, Fz, Cz, T8, P7, P8, C3, C4, C3, CP2, CP4, CP1, CP6, CP5, P3, P4, PZ, O1, O2, and POz) to the cerebral cortex in a constant spatial arrangement.

Using conductive gel, the impedance of each electrode was kept below 10 kΩ. To get as much artifact-free EEG data as possible, all participants were instructed to close their eyes, relax, and allow their thoughts to wander during the EEG data gathering process. The subjects were seated in a comfortable position and this cap was placed on the subjects' head. Before acquiring the EEG data, the subjects were instructed to maintain a comfortable relaxed seated position. The laptop screen was placed at a distance of 80 cm away from the subjects viewing angle.

Fig 3.5: A subject with EEG head cap system

The figure (3.6) shows the schematic configuration of 32 EEG channels arranged in an extended 10–20 layout. Colors indicate four regions of interest (ROIs) per hemisphere: frontal (F, pink), fronto-temporo-central (FTC, blue), centro-parietal (CP, green), and parieto-occipital (PO, yellow). Midline channels Fz, Cz, Pz, and Oz were not part of any region of interest. CMS and DRL indicate locations of reference and ground electrodes, respectively.

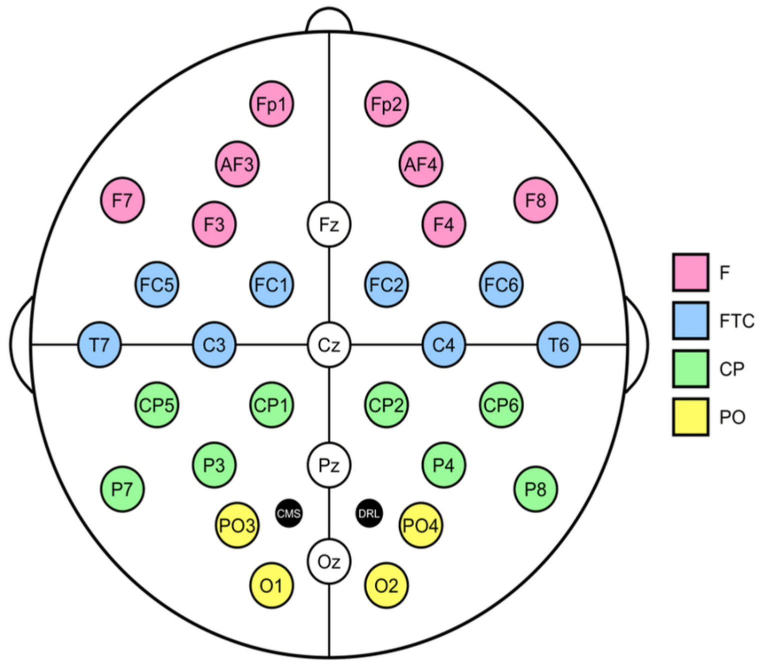

Fig 3.6: Electrode Positioning

3.5 PREPARATION OF CONDUCTIVE GEL SOLUTION

When a gel containing many chloride ions is applied between the skin and this electrode, conduction is improved and the skin-electrode interface impedance is reduced. Therefore, the gel between the skin and electrode allows for good quality recording of biopotentials. This study 2tbsp of KCl, plus 2-3 drops of baby shampoo with 1 liter of distilled water is used to prepare a conductive solution gel. The electrodes are kept inside the solution for 20 minutes and then the readings are taken.

CHAPTER 4: DATA ACQUISITION

4.1 DATA COLLECTION PROTOCOLS

Data acquisition is the process of converting real-world signals to the digital domain for display, storage, and analysis. Because physical phenomena exist in the analog domain, i.e., the physical world that we live in, they must be first measured there and then converted to the digital domain. The acquisition process is very important process in determining the wave singles.

In this study the EEG signals are acquired using five acquisition protocols comprising different types of stimuli which includes resting state visually evoked potentials, steady state visually evoked potentials and auditory evoked potentials. Consented EEG signals were obtained from the 42 subjects (8 males and 34 females) between the age group of 20 to 50 years). The signals were recorded in the closed room away from the external disturbance. The EEG signal acquired using an R-NET cap from the brain product consisting of thirty-two passive electrodes along with the one ground and a reference electrode, sampled at 250 Hz frequency.

The subjects were seated in a comfortable position and this cap was placed on the subjects' head. Before acquiring EEG data, the subjects were instructed to maintain a comfortable relaxed seated position. Subjects were also instructed to avoid the use of phones and body movements. the subjects were also asked to focus their attention on the videos comprising of set of audio instructions and, different video clips and images that was presented to them through five Data Acquisition Protocols (ADP). The laptop screen was placed at the distance of 80cm away from the subjects viewing angle. The total experiment is of 12 min 7 sec and it was divided into five protocols. Each protocol is discussed in the next section.

4.2 DESCRIPTION OF THE ACQUISITION PROTOCOLS

When assessing the quality of the brain wave signal, the acquisition step is a crucial procedure. There are five distinct data acquisition protocols, each containing a variety of stimuli such as resting state (RS), visually evoked potential (VEP), auditory evoked potential (AEP) and steady state visually evoked potential (SSVEP) are used in this study to capture the EEG signals. These triggers are chosen to capture the subject's interest, boost the signal to noise ratio (SNR), and produce meaningfully distinct patterns in response to various stimuli.

4.2.1 Protocol 1

The total duration of the first protocol lasts for 2 minutes and 23 seconds, with the 3-seconds of introduction about the protocol. This approach is known as a "resting stimuli test," wherein subjects are required to be calm and relaxed and then they have to follow the instructions (eg. closing and opening of the eyes). The subjects were seated in a comfortable position at a distance of 80cm away from the screen and the cap was mounted on the subjects' head. The EEG signals were recorded. According to the instruction the subjects has to closed their eyes for 30 seconds and then open their eyes for 10 seconds. this procedure was done for two times are the data was collected.

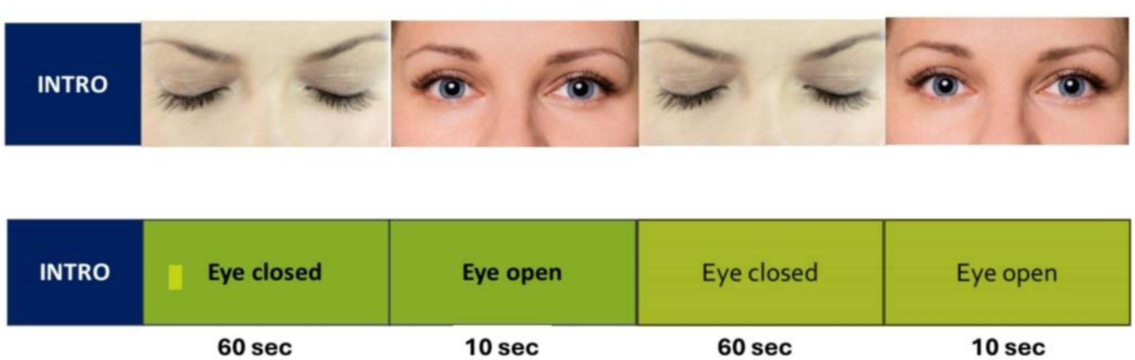

Fig 4.1: Timing Diagram of Protocol – 1

4.2.2 Protocol 2

The total duration of the second protocol is a 1 minutes and 50 seconds. Participants in this technique, known as "An Optical Illusion Eye Test," must identify the unusual figure in the provided image. This test requires keen observation skills to uncover them. this exercise not only test our visuals perception but also taps into our cognitive abilities, including attention details and pattern recognition.

In this test there are three distinct photos correspond to each of the three tiers in which participants have to identify the unusual figure within the given time. the complexity of the figures will increase as increase in the level. There are total three levels, with 30 seconds of time to perform each and 10 seconds of break in between. In this test Participants' anxiety levels rises in proportion to the level, and those signals are recorded.

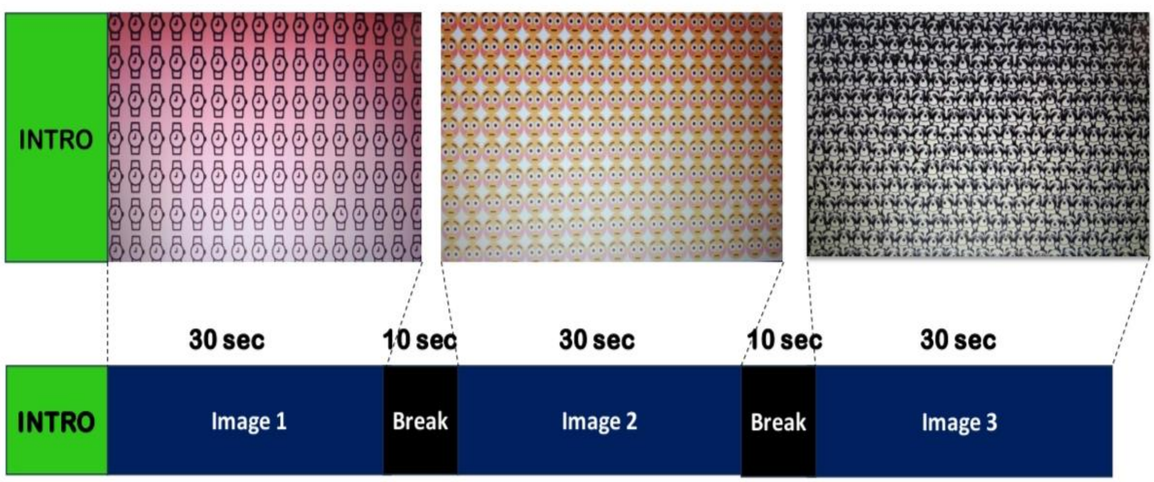

Fig 4.2: Timing diagram of Protocol-2

4.2.3 Protocol 3

The third protocol consisted of a Stroop test comprising typical tasks that have been used to induce stress in many previous researches [32] and the publication was one of the most cited works in the field of experimental psychology [33]. The aim of this test was to determine the color of the text. If the color of the text and the text did not match (e.g., the word “green” printed in blue font, or “red” printed in green) a subject who was asked to specify the color of the text was going to perform it more slowly and with a greater probability of error than if the text and its color were compatible (see Figure 4). Every next scene was more stressful (more difficult) and it was directly followed by relaxation scene.

The total duration of the second protocol is 2 minutes and 2 seconds. The test was divided into three levels with 14 seconds of instructions. First round is consist of 46 seconds, second round is consist of 36 seconds and third round is of 26 seconds. It is used to measure a person's selective attention capacity and skills and processing speed and the data was collected.

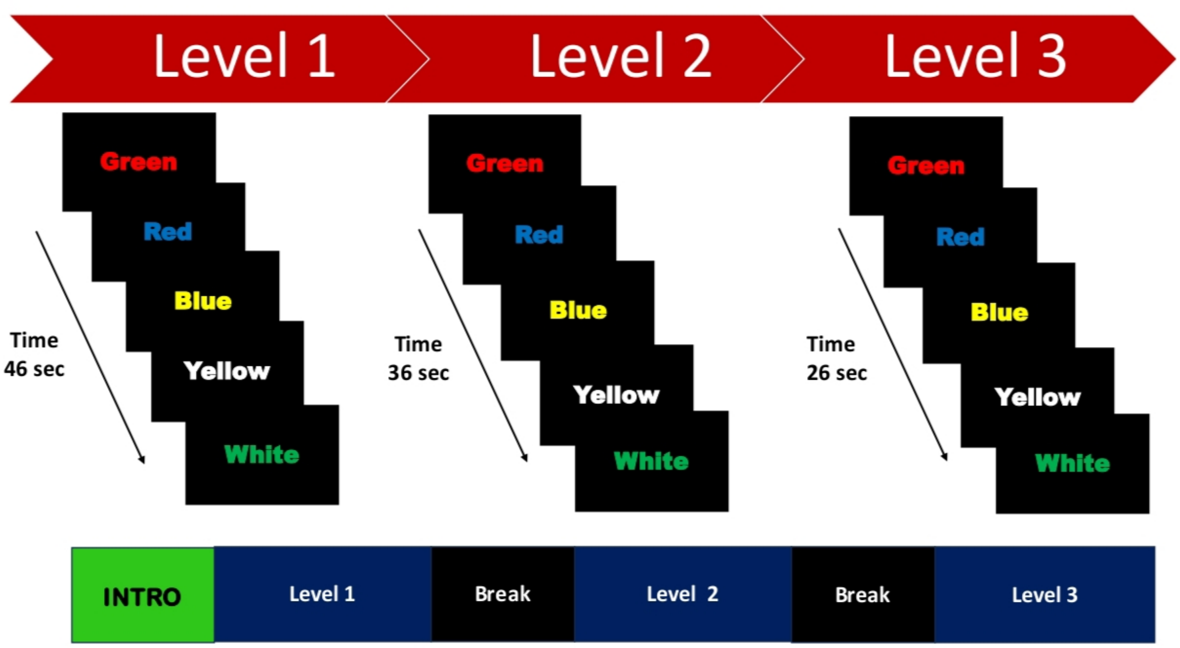

Fig 4.3: Timing diagram of Protocol – 3

4.2.4 Protocol 4

There is a 1 minutes 50 seconds procedure in the fourth protocol. Participants in this technique, known as "An Auditory Evoked Potential Test," is performed with closed eye in the fourth protocol. In this protocol the participants are paying attention on the musical sound of different frequencies.

In this an Auditory Evoked Potential Test participants are instructed to closed their eyes and sit relaxed. Then the participants are provided with the different musical sound of instruments having different frequencies. There are total three sound tract of 30 seconds each with 10 seconds of break in between. the first sound track is consist of Flute followed by Piano and Sitar instruments.

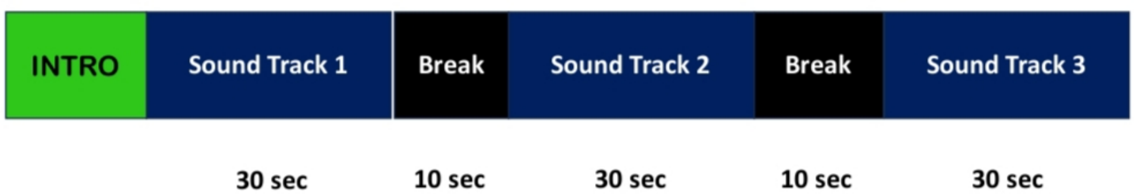

Fig 4.4: Timing diagram of Protocol - 4

4.2.5 Protocol 5

The last procedure permits the participants to see a 3 minutes 47 seconds virtual reality video. The test is referred regarded as a visual auditory evoked potential test (VEEP test) because it allows participants to both see and listen to the movie, which has a greater impact than either visual or auditory evoked potential alone. the video consist of different kinds of emotions like fear, tensed, relaxed etc. which ignite the participant emotions and make them anxious.

Fig 4.5: Timing diagram of Protocol-5

All the Data Acquisition protocols were used to collect the data from the subjects in the closed room where subjects are not distracted with the external disturbance.

CHAPTER 5: METHODOLOGY

5.1 EEG DATA PRE-PROCESSING

The process of getting raw data ready for a machine learning model is called data preprocessing. It is the initial and most important stage in the development of a machine learning model. Not all of the time do we find clean, prepared data while starting a machine learning project. Additionally, cleaning and formatting data is a must for every process using it. Thus, we employ the data preparation task for this data.

Real-world data typically has errors, missing numbers, and may be in an unusable format that prevents machine learning models from being applied directly. Cleaning the data and preparing it for a machine learning model are necessary steps in the data preparation process, which also improves the machine learning model's accuracy and efficiency. it involve below steps:

- Getting the dataset
- Importing libraries
- Importing datasets
- Finding Missing Data
- Encoding Categorical Data
- Splitting dataset into training and test set
- Feature scaling

A dataset is the first thing I need in order to develop a machine learning model because these models rely entirely on data to function. A dataset is a collection of data that has been properly formatted and gathered for a specific topic. Dataset used for different purposes are of different formats. In my study, the high density EEG data (EDF) which is directly retrieved from the R-Net EEG system were converted to {.mat} files. After converting into .mat file the whole data is segmented into five different segments namely, Protocol-1, Protocol-2, Protocol-3, Protocol-4 and Protocol-5, having 5 different time-line. There are various artifacts observed during the recording of EEG signals, to clean the data in my study a band-pass filter and notch filter with a filtering frequency range of 0.3 to 70 Hz were used to pre-process the data.

5.2 FEATURE EXTRACTION METHODS

In machine learning and data analysis, feature extraction is the process of finding and removing pertinent characteristics from unprocessed data. These characteristics are then employed to provide a more illuminating dataset, which may then be applied to a number of different activities, including: Classification, prediction and clustering. The goal of feature extraction is to extract as much pertinent information as possible while reducing the complexity of the data (sometimes referred to as "data dimensionality"). This facilitates the process of analysis and enhances the effectiveness and efficiency of machine learning algorithms. In order to distinguish and make it easier to utilize useful characteristics from irrelevant ones, feature extraction may entail the generation of new features (a process known as "feature engineering") and data modification.

Feature extraction plays a vital role in many real-world applications. The relevant characteristics are "extracted" from the irrelevant ones through the process of feature extraction. The dataset gets simpler and the analysis's accuracy and efficiency rise when there are fewer characteristics to process. Features extraction is a critical part of the processing of EEG signals. The techniques have been conducted in different domains such as frequency features, time-frequency features, statistical features, entropy-based features and higher-order crossing (HOC) features. Zeynali et al. [28] proposed a modality for decreasing the error of the EEG-based key generation process by using Discrete Fourier Transform, Discrete Wavelet Transform, Auto-Regressive Modelling, Energy Entropy and Sample Entropy. Petrantonakis [29] applied HOC feature extraction analysis on EEG data to recognize emotions.

In this study all the analysis were performed in Matlab (version R2023b) software. There are a variety of methods used to extract the feature from EEG signals, among these methods are Fast Fourier Transform (FFT), Wavelet Transform (WT), Time Frequency Distribution (TFD), EigenVector methods (EM), Auto Regressive methods (ARM) and so on. I used five different feature extraction techniques which are used to analyzed the data. Among these methods I have used Fast Fourier Transform (FFT), Discrete Wavelet Transform (DWT), Welch Method, Principal Component Analysis (PCA) and Extract features extraction techniques, out of which Welch Method and Discrete Wavelet Transform (DWT) shows the highest accuracy compared to the rest, and Principal Component Analysis (PCA) shows the least accuracy.

For feature extraction the EEG data matrix was divided into train and test sets using the 10-CV. The train and test sets were maintained apart by the 10-CV iterations, and only the training data was used for the constructing classification model and feature selection. There are total five feature extraction methods were used. Thus, the process of selecting features and building the classification model was carried out.

5.3 CLASSIFICATION METHODS

A supervised learning method called the classification algorithm is used to determine the category of fresh observations based on training data. In the process of classifying new observations, a software first divides them into a variety of classes or groups after learning from the provided dataset or observations. For example, cat or dog, 0 or 1, yes or no etc. Classifications are sometimes known as labels, goals, or categories. There are different classification methods used for data. The main goal of the Classification algorithm is to identify the category of a given

the EEG data. The EEG data matrix was divided into train and test sets using the 10-CV. The train and test sets were maintained apart by the 10-CV iterations, and only the training data was used for the constructing classification model and feature selection. All the analysis were done using Matlab (version R2023b) software.

EEG dataset, and these algorithms are mainly used to predict the output for the categorical data. The algorithm which implements the classification on a dataset is known as a classifier. There are two types of Classifications:

- Binary Classifier: A classification problem is said to as binary if there are only two feasible solutions. Ex: YES or NO, MALE or FEMALE, CAT or DOG, SPAM or NOT SPAM, and so on.
- Multi-class Classifier: A classification issue is referred to be a multi-class classifier when there are more than two possible results. Ex: different crops and musical genres are classified.

In this study two classifier model are used namely Support Vector Machine (SVM) and Convolutional Neural Network (CNN).

Support Vector Machine (SVM):

One of the most widely used supervised learning techniques for both classification and regression issues is Support Vector Machine, or SVM. In order to make it simple to classify fresh data points in the future, the SVM method seeks to identify the optimal line or decision boundary that may divide n-dimensional space into classes. We refer to this optimal decision boundary as a hyperplane. SVM selects the extreme vectors and points to aid in the creation of the hyperplane. The technique is referred regarded as a Support Vector Machine since these extreme situations are known as support vectors.

To maximize the distance to give some space to the hyperplane is the main idea behind SVM. The goal is to maximize the minimum distance is given by:

$$d_H(\phi(x_0)) = \frac{|w^T(\phi(x_0)) + b|}{||w||_2}$$

$$w^* = arg_w max \, [min_n \, d_H(\phi(x_n))]$$

While making the predictions on the training data which were binary classified as positive and negative groups, if the point is substituted from the positive group in the hyperplane equation, we will get a value greater than 0 (zero), Mathematically,

$w^T(\Phi(x)) + b > 0$

And predictions from the negative group in the hyperplane equation would give negative value as

$w^T(\Phi(x)) + b < 0.$

But here the signs were about training data, which is how we are training our model. That for positive class, give a positive sign and for negative give a negative sign.

But while testing this model on test data, if we predict a positive class (positive sign or greater than zero sign) correctly as positive, then two positives makes positive and hence greater than zero result. The same applies if we correctly predict the negative group since two negatives will again make a positive.

But if the model miss classifies the positive group as a negative group then one plus and one minus makes a minus, hence overall less than zero.

Summing up the above concept:

The product of a predicted and actual label would be greater than 0 (zero) on correct prediction, otherwise less than zero.

$$y_n\left[w^T\phi(x) + b\right] = \begin{cases} \geq 0 \; if \; correct \\ < 0 \; if \; incorrect \end{cases}$$

For perfectly separable datasets, the optimal hyperplane classifies all the points correctly, further substituting the optimal values in the weight equation.

$$w^* = arg_w max \left[min_n \frac{|w^T(\phi(x_n)) + b|}{||w||_2} \right] = arg_w max \left[min_n \frac{y_n |w^T(\phi(x_n)) + b|}{||w||_2} \right] \because perfect \; seperation$$

Arg max is an abbreviation for arguments of the maxima which are basically the points of the domain of a function at which function values are maximized. The independent term of weight outside gives:

$$w^* = arg_w max \frac{1}{||w||_2} \left[min_n \, y_n \, |w^T \, (\phi(x) + b|\right]$$

The inner term ($\min_n y_n |w^T$ **Φ(x) + b** |) basically represents the minimum distance of a point to the decision boundary and the closest point to the decision boundary H.

Re-scaling the distance of the closest point as 1 i.e. ($\min_n y_n |w^T$ **Φ(x) + b** |) = 1. Here, the vectors remain in the same direction and the hyperplane equation will not change.

Re-scaling of distance is given by:

$$w \rightarrow cw \,,\, b \rightarrow cb$$

$$(cw)^T \phi(x_n) + (cb) = c\left(w^T \phi(x_n) + b\right) = 0$$

The **equation now becomes** (describing that every point is $$at least 1/||w||2 distance apart from hyperplane) as

$$w^* = arg_w max \frac{1}{||w||_2} \quad , s.t. \ \min_n y_n \left[w^T \phi(x_n) + b \right] = 1$$

This maximization problem is equivalent to the following minimization problem which is multiplied by a constant as they don't affect the results.

.

A convolutional neural network (CNN) is a type of deep learning neural network architecture commonly used for computer vision. When it comes to Machine Learning, Artificial Neural Network perform really well. Neural Networks are used in various datasets like images, audio, and text.

Different types of Neural Networks are used for different purposes. In this study both the classifier model is used to analyzed the data. Although CNNs are predominantly used to process images, they can also be adopted to work with audio and other signal data. CNN architecture is inspired by the connectivity pattern of the human brain – in particular, the visual cortex , which plays an essential role in perceiving and processing visual stimuli. In CNN classifier I used 11 filters which gave good accuracy with the 10 cross- validation of data and the test and train data were processed and classified.

CHAPTER 6: RESULTS AND ANALYSIS

6.1 Results:

In this section the experimental outcome of the study is summarized. The standard EEG procedure was based on the analysis of the response to specific stimuli. I present the experiment based on the two EEG biometric verification methods: Support Vector Machine (SVM) and Convolutional Neural Network (CNN) using EEG database of 42 subjects. In this work I performed two different EEG verification algorithms using five Data Acquisition Protocols. Below tables shows the performance of the different classifier.

Table 1: Performance verification of SVM method using Data Acquisition Protocols showing Accuracy and standard deviations

Protocols / Brain waves	Protocol - 1	Protocol - 2	Protocol – 3	Protocol - 4	Protocol – 5
Gamma	61 ± 14.4914	57.7368 ± 12.9071	44.6364 ± 7.0574	43.6364 ± 6.0644	44.6364 ± 7.0575
Beta	61 ± 14.4914	53 ± 14.9366	43.6364 ± 6.0644	43.6364 ± 6.0644	43.6364 ± 6.0644
Alpha	63.6364 ± 6.0644	53 ± 14.9366	43.6364 ± 6.0644	43.6364 ± 6.0644	43.6364 ± 7.0574
Theta	60.5 ± 13.6321	53 ± 14.9366	44.6364 ± 7.0574	44.6364 ± 7.0574	43.6364 ± 6.0644
Delta	61.5 ± 13.6321	51.9474 ± 13.6308	44.1818 ± 7.7608	43.6364 ± 6.0644	44.6364 ± 7.0574

In SVM method protocol – 1 shows the highest accuracy and protocol – 4 shows the least accuracy among the rest of the protocols. This shows that protocol – 1 that is the "resting stimuli test," where the subjects are seated in a comfortable position were calm and relaxed following the instructions of closing and opening of their eyes give good results then the rest of the protocols. As we can see from the table that alpha wave is very active in protocol – 1.

Alpha rhythm blocking, which is the increase of brain signals amplitude in alpha bands due to closure of the eyes in a wakeful condition, is used to detect blinks at various channels and eye closing or opening procedure has the widespread effects on overall EEG electrodes. The eye blinking signal is very low frequency signal of range 1- 13 Hz. It has been reported that the normal spontaneous blink rate is between 12 and 15/ min. A mean blink rate of up to 22blinks / min.

As the protocol – 1 is of opening and closing of eye the variation in the brain wave can be seen and showing alpha wave frequency as the prominent frequency.

Table 2: Performance verification of CNN method using Data Acquisition Protocols showing Accuracy and Standard deviation of the data.

Protocols / Brain waves	Protocol – 1	Protocol – 2	Protocol – 3	Protocol – 4	Protocol – 5
Gamma	51.5000 ± 7.4722	46.5000 ± 7.4722	51.5000 ± 10.8141	51 ± 10.4881	48.5000 ± 10.8141
Beta	47 ± 12.0646	44 ± 6.5828	46 ± 8.4324	43 ± 11.1056	40 ± 7.0711
Alpha	51 ± 12.2020	47 ± 13.1656	47 ± 14.5678	52 ± 11.5950	52.5000 ± 7.9057
Theta	41 ± 12.6491	50.5000 ± 7.6194	42.5000 ± 10.3414	51 ± 12.4276	44 ± 9.6609
Delta	46 ± 7.7460	57.5000 ± 9.7895	47 ± 7.1492	43 ± 10.3280	48.5 ± 12.0301

In CNN method protocol – 2 shows the highest accuracy and protocol – 5 shows the least accuracy among the rest of the protocols. The protocol – 5 consist of the video of virtuality. The video create a scarry, intense, fearful and relaxing stimuli in it. On the other hand it shows that protocol – 2 known as "An Optical Illusion Eye Test," require keen observation skills in which the participants must identify the unusual figure in the provided image within the specific time, theta waves and the edge of the delta waves are strong during internal focus shows the best result among the rest of the protocols.

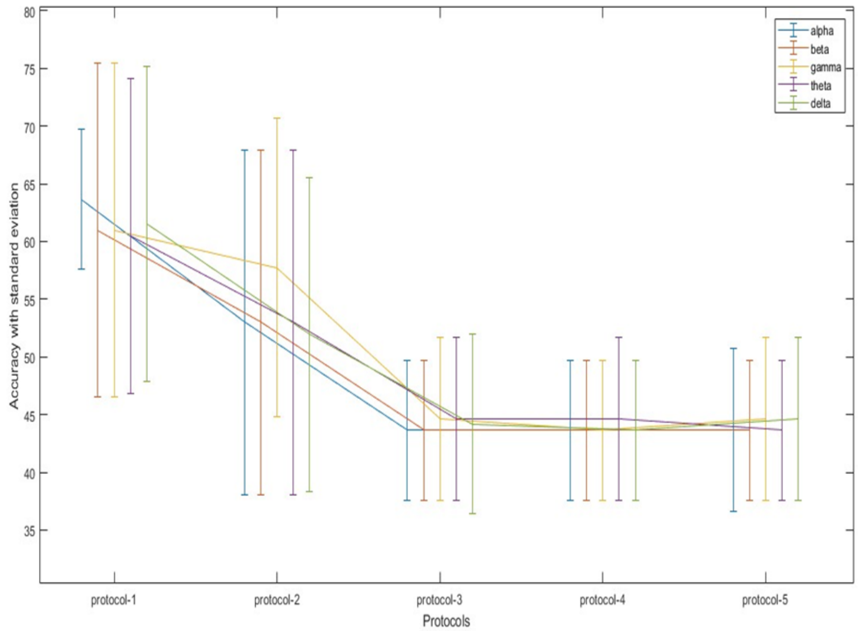

Fig 6.1 : Performance verification plot of SVM method showing accuracy with standard deviation

This graph shows the alpha, beta, gamma, theta and delta waves of the Data Acquisition Protocols – protocol-1, protocol-2, protocol-3, protocol-4 and protocol-5. It shows that protocol – 1 has the highest accuracy among the rest of the protocol with the less standard deviation. It also shows that alpha wave performed better and it is having highest accuracy and least standard deviation comparatively from the other waves in all the protocols. In protocol – 2 gamma is having the highest accuracy and alpha wave is having the least. In protocol – 3 alpha is having maximum and delta is having minimum accuracy. In protocol - 4 all having similar accuracy accept theta. And in protocol - 5 beta is having maximum accuracy and alpha is having minimum accuracy.

If I compare all the protocols, acquisition data of protocol – 2, Protocol – 3 and Protocol – 5 are showing more reliability compare to protocol -1 and protocol – 2.

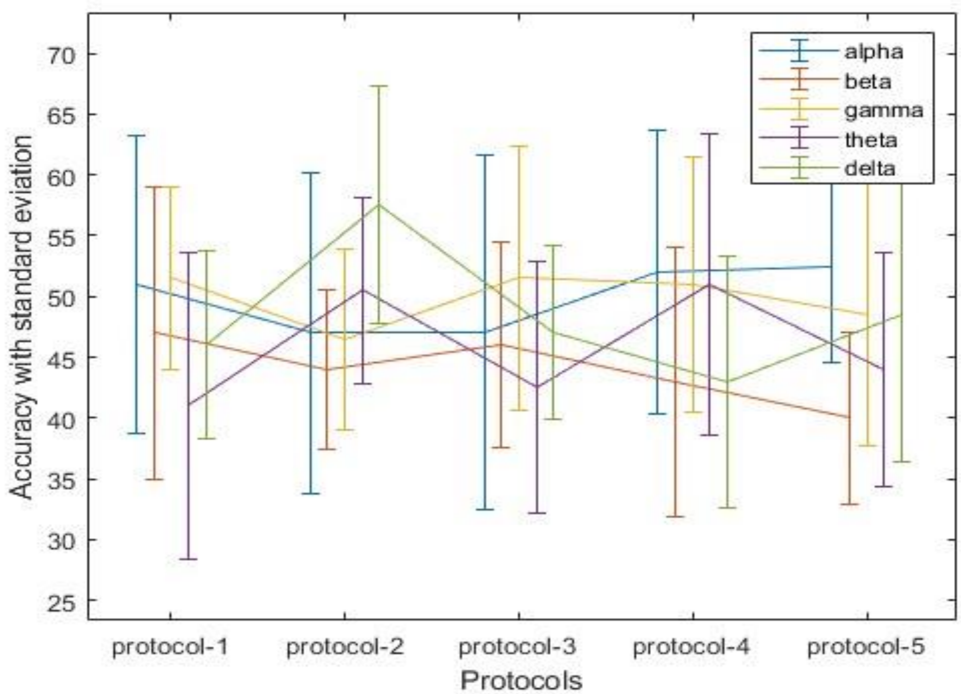

Fig 6.2: Performance verification plot of CNN method showing accuracy with standard deviation

This graph shows the alpha, beta, gamma, theta and delta waves of the Data Acquisition Protocols – protocol-1, protocol-2, protocol-3, protocol-4 and protocol-5. It shows that protocol – 2 has the highest accuracy among the rest of the protocol with the less standard deviation.

If we compare brain waves of protocol – 1 , gamma wave have the highest accuracy. In protocol – 2 , delta wave have the highest accuracy. In protocol – 3, gamma wave have the highest accuracy. In protocol – 4, alpha wave have the highest accuracy. In protocol – 5, alpha wave have the highest accuracy. The overall performance of alpha wave has the highest accuracy with high standard deviation. The beta wave shows the low accuracy compare to alpha but it has low standard deviation.

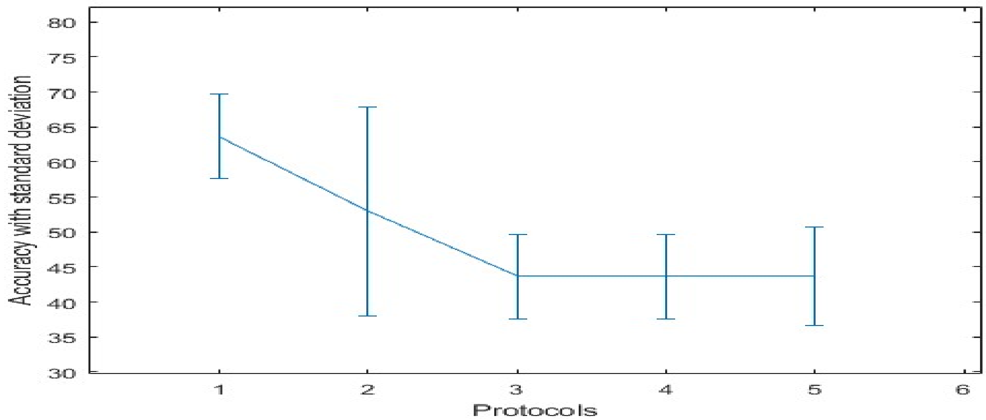

Fig 6.3: Performance plot of alpha wave of the EEG acquisition protocols using SVM

The above plot shows the point of the single alpha wave of the data acquisition protocol. This graph is obtained by using validation of 10 – cross validation method using SVM classifier. This graph depicts that protocol – 1 shows the highest accuracy with minimum standard deviation.

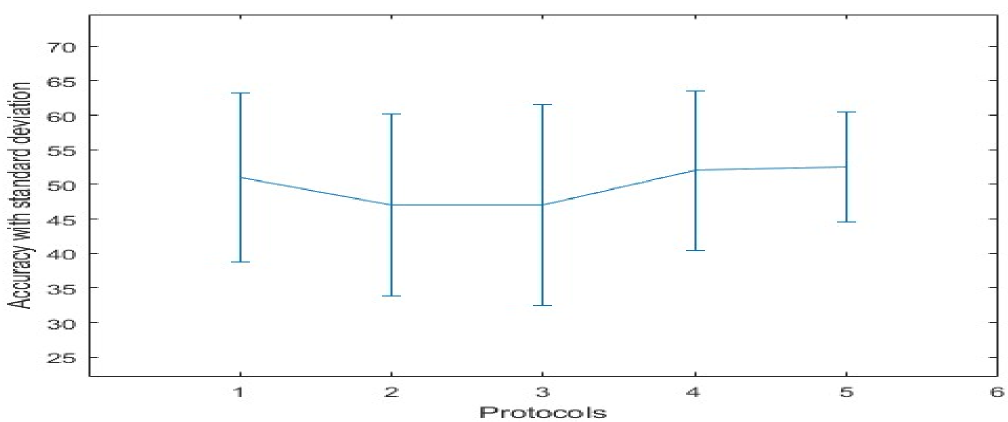

Fig 6.4 Performance plot of alpha wave of the EEG acquisition protocols using CNN

The above plot shows the point of the single alpha wave of the data acquisition protocol. This graph is obtained by using validation of 10 – cross validation method using CNN classifier. This graph depicts that protocol – 5 shows the highest accuracy with minimum standard deviation.

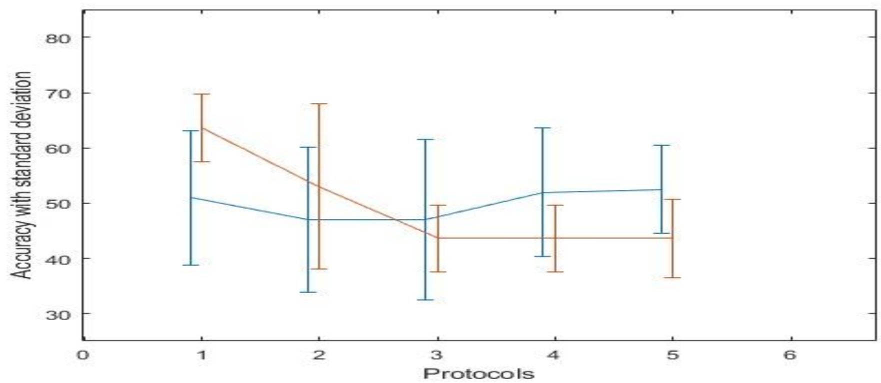

Fig 6.5: shows the comparison of alpha wave between SVM and CNN classifier.

Fig (6.5) shows the performance of the alpha wave using SVM and CNN method. As we can analyze from the graph that accuracy of protocol 1 shows high accuracy with less standard deviation in SVM and in protocol 2 SVM classifier shows higher accuracy but standard deviation is more. In protocol 3, 4 and 5 accuracy of protocols in CNN is higher than the SVM. Although CNN is having higher accuracy still SVM perform well as it has least standard deviation.

6.2 CONCLUSION:

The use of brain-wave signals for biometric verification has gained significant attention in recent times because of the vulnerability of conventional biometric modalities to presentation attacks. Analyzing the recorded brainwave patterns to identify abnormalities or specific patterns associated with various neurological condition has created significant attention of the researchers.

In this paper, I investigated the use of EEG signals to classify a subject's stress level while using different stimuli along with a VR video. For this purpose, I created a five simulation with relaxation scenes based on psychotherapy treatment. The experiment was conducted on a group of 42 subjects with 20 healthy adult volunteers and 22 anxiety volunteers comprising of 34 females and 8 whose EEG signal was continuously monitored using the R - NET EEG head cap system. Then, I classified the stress level using CNN and SVM algorithms among them SVM shows higher performance accuracy then CNN. The obtained results were promising and a further study is greatly encouraged.

Participants in the post-interview acknowledged that the developed of these method used in the virtual environment was excellent for relaxation. Some participants pointed out that the prepared 'stressful' tasks induced a state of focus rather than a state of nervousness. This could have directly affected the deterioration of the later stage classification results. Therefore, a more detailed participant survey should be used in future studies.

However, the average results were slightly lower than in the earlier stage of analyses. It may have been caused by the amount of data. Since the amount was relatively small, the CNN was more difficult to train and apply. To summarize, we had a lot of concerns about measuring EEGs with the R – NET head cap from brain products, since it required an intricate process of applying the gel for EEG measurements. Although the stimuli experience required stillness from the user, some of the recordings were rejected for further analysis due to the low quality.

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