AN AUTOMATED FRAMEWORK FOR STRESS RECOGNITION AND EMOTION DETECTION USING MACHINE LEARNING ALGORITHMS

Thesis Submitted for the Award of the Degree of

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in

Computer Science and Engineering

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DECLARATION

I, hereby declare that the presented work in the thesis entitled **"AN AUTOMATED FRAMEWORK FOR STRESS RECOGNITION AND EMOTION DETECTION USING MACHINE LEARNING ALGORITHMS"** in fulfillment of the degree of **Doctor of Philosophy (Ph. D.)** is outcome of research work carried out by me under the supervision of **Dr. Nishant Agnihotri**, working as Assistant Professor, in the **School of Computer Science and Engineering of Lovely Professional University, Punjab,** India. In keeping with the general practice of reporting scientific observations, due acknowledgements have been made whenever the work described here has been based on the findings of other investigators. This work has not been submitted in part or full to any other University or Institute for the award of any degree.

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CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled **“AN AUTOMATED FRAMEWORK FOR STRESS RECOGNITION AND EMOTION DETECTION USING MACHINE LEARNING ALGORITHMS”** submitted in fulfillment of the requirement for the reward of degree of **Doctor of Philosophy (Ph.D.)** in the School of Computer Science and Engineering, is a research work carried out by **Hole Komal Rajendra,** 41900254, is bonafide record of her original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.

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ABSTRACT

In today's contemporary culture, the high incidence of stress and emotional disorders has developed into a major cause for worry, stressing the need for preventative screening and treatment. EEG signals provide helpful insights into these disorders because they capture patterns of brain wave activity that are related to different types of stress and emotional states. Nevertheless, categorizing EEG data for anticipatory detection in an effective manner continues to be a difficult task.

In this thesis, we offer innovative methods for effective EEG categorization, to enable the early diagnosis of emotional disorders and stress-related conditions. The findings of the study are provided in the form of two separate publications, each of which focuses on a certain area of EEG data processing and categorization.

The first piece of research presents a multispectral data representation engine to enhance the classification performance of EEG signals via the use of ensemble models. Traditional deep learning models often depend on data from a specific domain, which restricts their applicability to a wide range of illness classifications. In addition, the procedures for the selection of features and their extraction often lack transparency and control in these models. To circumvent these restrictions, the engine presented here makes use of Mel Frequency Cepstral Components (MFCC) in conjunction with iVector components to accurately represent EEG signals. While the iVector is built with the use of statistical entropy characteristics, the MFCC feature vector includes cepstrum, spectrum, power density, and other frequency domain datasets & samples. By using these supplementary sets of features, the engine can achieve improved feature representation efficiency, which ultimately results in improved classification performance. To determine how well it works, a unique ensemble classification model that is capable of categorizing EEG data into numerous illness categories, such as dementia, stroke, brain tumors, and sleep disorders, has been created. This model is built on multiple neural networks, which are referred to as MNNs. The results of our experiments show that our suggested model is more accurate than the state-of-the-art approaches in terms of accuracy, precision, recall, and delay performance. The model achieves a classification accuracy of over 98.5%

when applied to a variety of EEG illnesses. Because of these benefits, the suggested model is a good candidate for use in clinical applications that take place in real-time.

The second body of study is on the development of a Transfer Learning-based Bioinspired Ensemble Model for the proactive diagnosis of emotional disorders and stress-related conditions. When applied to a wide variety of diseases, the currently available EEG processing models either have a high degree of complexity or a lesser degree of accuracy. To overcome these constraints, the model that we have suggested integrates transfer learning strategies as well as a bioinspired ensemble structure. EEG datasets of different types are processed to extract multispectral features. These features include MFCC, iVector, Cosine, Fourier, and Wavelet components. These characteristics are put through a feature selection procedure that is based on Grey Wolf Optimization (GWO), to increase the amount of inter-class feature variation across a variety of stress and emotional disorder classes. The chosen features are then converted into a two-dimensional representation and run through a transfer learning-based Convolutional Neural Network (CNN) model. This model is a combination of the ResNet 101, Mobile V Net, and YoLo models. The classification results that were obtained are then placed through a process known as ensemble classification, which involves merging several types of models such as Naive Bayes (NB), Support Vector Machine (SVM), Deep Forest (RF), Logistic Regression (LR), and Multilayer Perceptron (MLP). Post-processing tasks, such as identifying the probability of illness transmission and estimating the likelihood of future infections, are also carried out by these classifiers. The experimental evaluations that were carried out on the DEAP (Database for Emotion Analysis Using Physiological Signals) and Interface datasets demonstrate that our proposed model has a superior performance in comparison to state-of-the-art methods. Specifically, our proposed model has an 8.5% higher accuracy, 8.3% higher precision, 5.9% better recall, 4.5% better area under the curve (AUC), and 14.9% faster classification performance. The significance of these findings lies in the fact that they highlight the clinical applicability of our paradigm.

In general, this thesis makes a contribution to the development of effective EEG categorization for the early diagnosis of emotional disorders and stress-related conditions. Both the multispectral data representation engine that was suggested and

the bioinspired ensemble model that was based on transfer learning provide innovative answers to the problems that are caused by the limits of current methods. In addition, the performance tests show that the models that are suggested are effective and superior in properly identifying a variety of EEG datasets & samples. To further improve classification performance in context-sensitive settings, future research may concentrate on verifying the models on new datasets and investigating the possibility of integrating hybrid bioinspired models or advanced deep learning approaches.

Keywords: *EEG; Stress; Bioinspired; Ensemble; GWO; ResNet; YoLo; MobileVNet.*

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Hole Komal Rajendra

Date:

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ABBREVIATION

ML	Machine Learning
SVM	Support Vector Machine
DT	Decision Trees
RF	Random Forests
ANN	Artificial Neural Networks
ECG	Electrocardiography
EMG	Electromyography
T	Temperature
BVP	Blood Volume Beat
SC	Skin Conductance
RSP	Respiration
FMRI	Functional Magnetic Resonance Imaging
GSR	Galvanic Skin Resistance
WT	Wavelet Transform
STFT	The Short-Time Fourier Transform
ICA	Independent Component Analysis
CWT	Continuous Wavelet Transform
RNN	Recurrent Neural Networks
CNN	Convolutional Neural Networks
LSTM	Long Short-Term Memory
ERPS	Event-Related Potentials
ROC	Receiver Operating Characteristic
GRU	Gated Recurrent Unit
DBN	Deep Belief Networks
LR	Logistic Regression
RBF	Radial Basis Function
LDA	Linear Discriminant Analysis
BLDA	Bayesian Linear Discriminant Analysis
BT	Bagging Tree
BCI	Brain-Computer Interfaces
LOSO	Leave-One-Subject-Out
FLDNET	Frame-Level Distilling Neural Network
HRV	Heart Rate Variability
MEG	Magneto Encephalography
IOT	Internet Of Things
NSD	Neonatal Seizure Detection
RSVP	Rapid Serial Visual Presentation
RCIT	Rapid Serial Visual Presentation And Concealed Information Test
BN	Batch Normalization
MF	Mindfulness Meditation
FNIRS	Functional Near-Infrared Spectroscopy
SNR	Signal-To-Noise Ratio

MFCC	Mel Frequency Cepstral Components
MNNS	Multiple Neural Networks
NNM	Neuroglial Network Model
LBPTH	Local Binary Pattern Transition Histogram
MSMM	Multivariable Scale Mixture Model
MSNNDC	Multiple Scaled Neural Network With Dilated Convolutions
DCNN	Deep Convolutional Neural Network
GWO	Grey Wolf Optimization
GRU	Gated Recurrent Unit
MSIN	Multi-Scale Inception Network
STM	Spatial And Temporal Matching
DTW	Dynamic Time Warping
LRELU	Leaky Rectilinear Unit
ROC	Receiver Operating Characteristic Curve

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CHAPTER 1

INTRODUCTION

"Most advances in science come when a person for one reason or another is forced to change fields."

- Peter Borden

Being in today's era, we are all surrounded by an environment that causes stress among various age groups of people. Mental pressure and stress have a wide adverse effect on an individual's life. It is very important to see if anyone is facing severe or acute stress because if it is kept unchecked then will be very hazardous**.** Stress recognition and emotion detection are pivotal in understanding human behavior and mental health. Traditional methods relying on subjective assessments or self-reports are often limited by biases and inconsistencies. In recent years, ML algorithms have emerged as powerful tools for objective and automated analysis of physiological and behavioral data, offering promising avenues for enhancing accuracy and scalability in stress and emotion assessment. These algorithms leverage features extracted from various physiological signals such as heart rate variability, skin conductance, facial expressions, and behavioral indicators including speech patterns and gesture analysis. Such multimodal data integration enables a holistic assessment of an individual's emotional state and stress levels.

This thesis focuses on the development of an automated framework designed to harness the capabilities of ML for real-time stress recognition and emotion detection. The framework aims to integrate multiple ML algorithms, including but not limited to deep learning models and ensemble methods. Each algorithm contributes uniquely to the robustness and interpretability of the overall system, accommodating diverse datasets and contextual variations.

1.1 OVERVIEW AND BACKGROUND

An electroencephalogram, or EEG for short, is a diagnostic examination that looks for deviations from typical brain electrical activity. Electrodes seen as metal discs having thin cables connecting to them, are applied to the scalp during this treatment. These electrodes detect diminutive electrical charges formed by the activation of brain cells. A graph is subsequently shown on a computer monitor by amplifying the electrical impulses that were captured. The comprehensive evaluation helps in identifying abnormalities or irregularities in the brain's electrical patterns. Evoked potential studies are related procedures that measure the brain's electrical activity in response to stimuli like sight, sound, or touch. These studies provide additional insights into specific aspects of brain function. EEG is particularly valuable in diagnosing various brain disorders [1] [2]. For instance, in cases of epilepsy, the EEG can reveal rapid spiking waves indicative of seizure activity. Individuals who have brain lesions due to disorders such as tumors or strokes may have EEG waves that are abnormally sluggish; the pattern will vary contingent on the lesion's size and location.

Alzheimer's disease, several psychoses, and narcolepsy, a sleep disorder, are among the additional conditions that can be diagnosed using this test. Beyond diagnosis, EEG serves other purposes such as assessing overall electrical brain activity, which can help assess the degree of brain damage in comatose patients, drug intoxication, or trauma. Additionally, it can be utilized to track blood flow to the brain during surgery. EEG is a useful and adaptable instrument for assessing the activity caused by the brain, helping healthcare providers diagnose a range of neurological conditions and monitor brain function in various clinical scenarios [3].

Detecting stress in EEG signals involves analyzing the electrical activity of the brain to find patterns or changes associated with stress. One way to do this is by looking at the EEG signals' power spectrum, which displays the energy distribution over several frequency bands like delta wave, theta wave, beta wave, and alpha wave. Stress might be linked to increased beta activity (related to alertness) and decreased alpha activity (associated with relaxation). Examining the temporal dynamics of EEG signals helps by identifying transient changes or spikes that might correspond to stress-inducing events. Features like statistical measures and spectral entropy, which capture the complexity of the signal, can be extracted from EEG data to indicate stress [1] [2] [3] [4].

Machine learning models that can be viewed to automate the procedure using SVM, DT, RF, or ANN can be instructed to classify EEG patterns into stressed and non-stressed categories. Pattern recognition techniques further aid in identifying distinct patterns in space which is spatial or time which is temporal within the EEG data associated with stress. Real-time monitoring of EEG signals allows for timely feedback on stress levels, which is valuable for applications like stress management or biofeedback [5]. Validation of diverse datasets and calibration ensure that stress detection models perform well across different populations and contexts. Ethical considerations, including user privacy and consent, must be addressed when collecting and analyzing EEG data for stress detection, complying with relevant regulations and guidelines.

Understanding that stress is a complex phenomenon, EEG signals provide only one aspect of the physiological responses to stress. Integrating information from various sources and considering contextual factors can amplify the stress detection models' precision and consistency. Collaboration with experts in neuroscience, psychology, and related fields contributes to a more comprehensive understanding of the patterns associated with stress in EEG signals. There are several ways to quantify stress, including EEG, ECG), EMG, T, BVP, SC, RSP, fMRI, GSR. Out of all the technologies that are accessible, EEG has been determined to be the most non-invasive method that yields accurate results [6].

1.1.1 Introduction to EEG Processing

The electroencephalogram is a method used in neurophysiology that does not need any intrusive procedures. This method captures the electrical activity of the brain using electrodes that are put on the scalp. EEG signals provide helpful insights into how the brain works and have been applied in a wide range of disciplines, including clinical diagnostics, neuroscience research, and brain-computer interface systems, amongst others. The representation of EEG is shown in Fig. 1.1 and the brain is electroded using the 10-20 placement approach as demonstrated in Fig 1.2. The examination of electrical brain activity, or EEG, signals is a critical stage in the process of gaining an understanding of the patterns of brain activity, identifying anomalies, and creating diagnostic tools for neurological disorders [7] [8]. Processing an EEG entails going through several procedures to glean useful information from the patterns of brain waves that were recorded. Preprocessing the signal, selecting, extracting, and classifying features are the stages that make up these phases. The total process of evaluating and comprehending the underlying brain activity is made easier by each step's contribution[9].

In a view of enhancing the signals' overall quality, Signal pre-processing is considered the first action in the EEG processing which is called pre-processing. This phase comprises eliminating noise and artifacts from the raw EEG datasets & samples[10]. EEG readings may be corrupted by a range of resources of noise, including ambient interference, muscle activity, eye blinks, and aberrations produced by electrodes. It is common practice to employ filtering techniques including notch, low-pass, and high-pass filters in preprocessing. These filters are used to remove noise components, while other preprocessing techniques, such as baseline correction, are used to remove artifacts [11]. After the signal has been pre-processed, the next stage is the extraction of features. Because of the complexity and multidimensionality of EEG information, it is very necessary to extract key features that can accurately capture crucial aspects of brain activity. The raw EEG signals are compressed and simplified into a more realistic feature space via the use of feature extraction algorithms. A variety of techniques can be applied for feature extraction, including analysis in the frequency domain, time domain, and time-frequency domain. The statistical aspects of the signal, such as its mean, its variance, and its skewness, may be reconstructed using time-domain features [12] [13], [14]. Among the details of the signal's spectrum content that may be discovered through the application of frequency-domain characteristics are power spectral density, spectral entropy, and specific frequency band power. The evolution of a signal's attributes over time can be observed with time-frequency analysis techniques like the WT or the STFT.

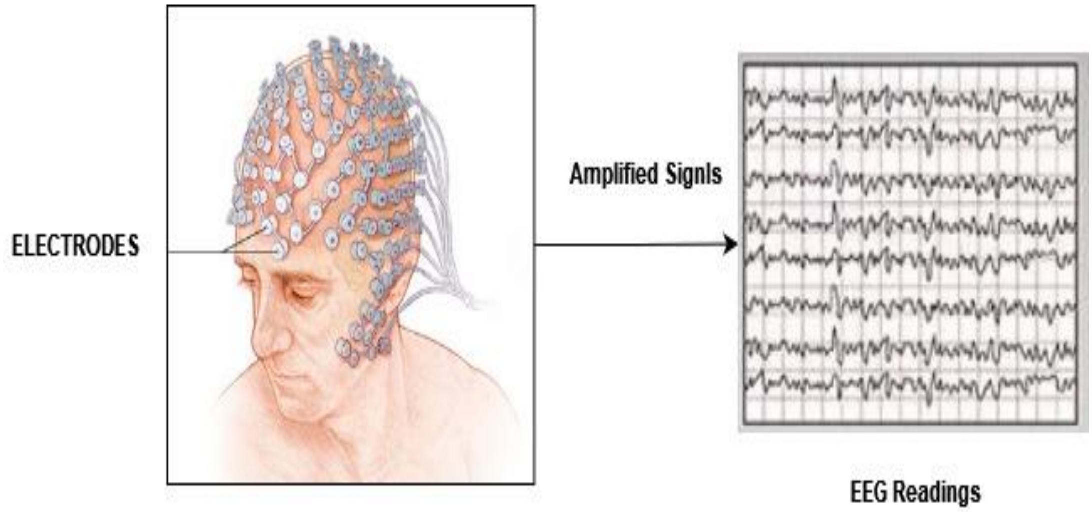

Figure 1.1 The Electroencephalogram

The next phase, which comes after extracting various features, is selecting features from them. Because EEG feature spaces have a high dimensionality, to reduce computing complexity and increase classification accuracy, it is imperative to select a subset of the most significant features. The valid intention of the many approaches used to choose characteristics is to determine which aspects are the most important in terms of discriminating between the various states or circumstances of the brain. These techniques may be based on statistical measurements, such as mutual information or t-tests, or they can apply optimization techniques including genetic algorithms or particle swarm optimization to locate the feature subset that has the greatest capacity for discrimination [15].

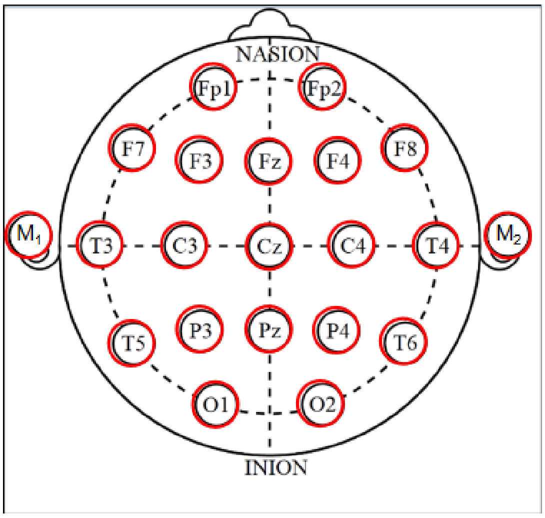

Figure 1.2 10-20 placement systems for EEG

In the last step, classification algorithms are used so that EEG signals may be placed into certain groups or classes based on the properties that were retrieved. The ability to classify data in EEG analysis is essential since it permits the identification of certain brain states as well as the diagnosis of neurological disorders. SVM, ANN, RF, and NB are only a few of the machine learning methods that are often utilized for EEG categorization. These algorithms generate models via the process of learning patterns from the labeled EEG data and can effectively categorize EEG signals that have not been observed [16], [17], [18]. Significant advancements have been made within the domain of EEG processing over the past few years. These advancements have been driven by the increased availability of computer resources, methods for machine learning, and the incorporation of domain knowledge. Because of these breakthroughs, the creation of more complex models and algorithms for EEG categorization has been made possible, which has led to increased diagnostic accuracy and the ability to implement these improvements in real-time [19].

In conclusion, several steps make up EEG processing, including feature extraction, feature selection, signal pre-processing, and classification, to evaluate and understand the complex brain wave patterns that are recorded by EEG datasets & samples. These procedures are described below. These processing phases are essential for establishing diagnostic tools for stress and emotional disorders, as well as for comprehending the activity of the brain, which may be used to locate issues for real-time scenarios. In the realm of stress and emotional disorders, the combination of cutting-edge computing approaches and machine learning algorithms has opened up new possibilities for fast and accurate EEG processing, opening the way for proactive identification and intervention processes.

1.1.2 Various components of EEG signals

The intricate waveforms of EEG signals show the electrical activity that happens in the brain. The signals from EEG offer crucial details about the mental states of the brain, the cognitive processes involved, as well as neurological disorders. Correct elucidation and examination of brain action depend heavily on it to have a solid understanding of the different components of EEG signals [20], [21], [22]. Different EEG bands with their respective frequency are mentioned in Table 1 and EEG brainwaves have appeared in Fig 1.3. This part will talk about the various components of EEG signals as well as the relevance of those components when it comes to EEG processing scenarios [23].

1. Delta Waves:
   Delta waves are oscillations of the EEG that occur at low frequencies and vary from 0.5 to 4 Hz. They are related to unconsciousness and the state of complete relaxation, and they are often seen during the deeper phases of sleep. The high amplitude and slow oscillations that are characteristic of delta waves are thought to be a reflection of the coordinated activity of huge groups of neurons.

Table 1.1 The EEG bands with a frequency range.

EEG Band Name	Frequency Bandwidth	Associated Brain State
Delta (**δ**)	**0.5Hz - 4Hz**	Deep Sleep, Unconscious
Theta (**θ**)	**4Hz - 8Hz**	Light sleep, Drowsy, recall

Alpha (**α**)	**8Hz - 13Hz**	Awake & resting, Relaxed, light meditation, super learning, conscious
Beta (**β**)	**13Hz - 30Hz**	Normal waking state, concentration, focus, Integrated, Engaged
Gamma (**¥**)	**30Hz - 54Hz**	Deep Meditation, the fastest brain activity

2. Theta Waves:

   Drowsiness, daydreaming, and light sleep are frequent times when the brain produces theta waves, which can range in frequency from 4 to 8 hertz. In addition, they are present during meditative states and certain mental activities. Memory formation, learning, and spatial navigation are all processes that are related to theta waves.

3. Alpha Waves:

   The range of frequencies for alpha waves is 8–13 Hz which is best noticeable when the eyelids are closed and the subject is in a relaxed yet awake condition. They are often seen positioned over the back parts of the brain. Alpha waves are typically utilized as a sign of tranquillity and decreased mental activity because they are connected with a state of wakeful relaxation and because they are produced when there is less mental activity.

4. Beta Waves:

   Beta waves are often noticed during active wakefulness and cognitive processing. Their frequency ranges from 13 to 30 hertz (Hz), and they are characterized by low amplitude. They are related to attentiveness, alertness, and active mental involvement on the participant's part. When doing activities that involve focus and the ability to solve problems, beta waves are often noticed.

5. Gamma Waves:

   Gamma waves are high-frequency oscillations of the EEG that vary from 30 to 100 Hz or even higher. They are linked to cognitive processes, sensory perception, and the integration of information across the many areas of the brain. Gamma waves are thought to play a part in bringing together many facets of sensory information and promoting coherent functioning in the brain.

6. The mu rhythm

   The mu rhythm is a distinct component of an EEG that may be seen across the sensorimotor cortex. It is distinguished by oscillations at alpha or beta frequencies (eight to thirteen hertz or thirteen to thirty hertz, respectively), and its activity decreases with voluntary movement or motor imagery. In the field of neurofeedback as well as brain-computer interface applications, the mu rhythm is often used.

7. Artifacts:

   Several different artifacts might taint EEG readings. These artifacts originate from non-neural sources. Eye blinks, eye movements, muscular activity, electrode artifacts, surrounding noise, and heart activity are some examples of the artifacts that may be present. The quality of EEG signals as well as their interpretation may be severely impacted by artifacts, which is why they need to be correctly recognized and deleted during the pre-processing stage.

Researchers and clinicians can evaluate patterns of brain activity, diagnose anomalies, and connect certain EEG components with cognitive processes or neurological disorders when they have a solid understanding of the many components that make up EEG signals. In the process of EEG processing, feature extraction techniques often entail examining the power, frequency, and temporal aspects of these components to collect significant information that can then be used for categorization and analysis [24], [25].

In conclusion, EEG signals are made up of a variety of components, such as delta-type waves, theta-type waves, alpha-type waves, beta-type waves, gamma-type waves, mu rhythm, and artifacts. Every one of these components indicates a different state of the brain, a particular cognitive activity, or an artifact. It is necessary to analyze these components to derive relevant characteristics, recognize problems, and gain knowledge of how the brain works. The proper identification and analysis of these components help the accurate processing of EEG data, which in turn makes it easier to diagnose and treat emotional disorders and stress-related conditions.

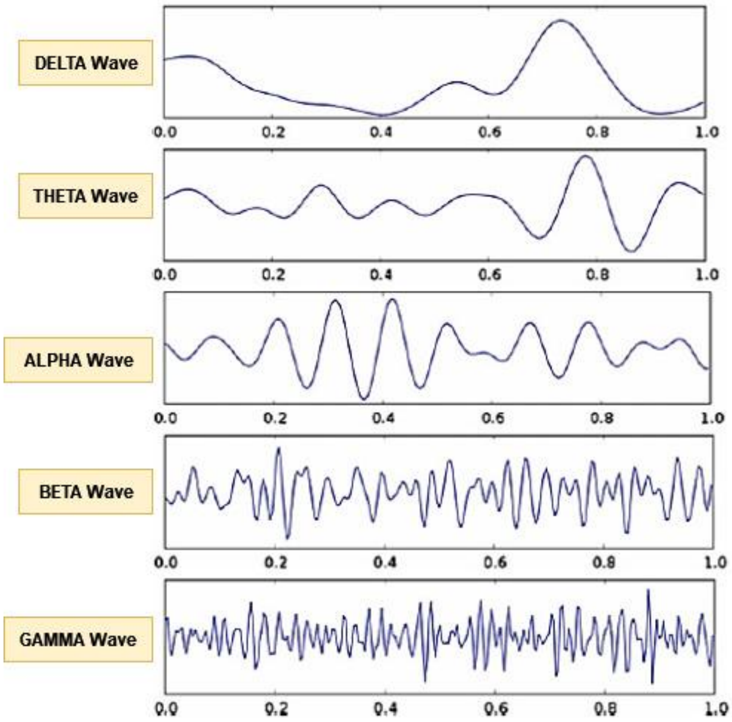

Figure 1.3 EEG brainwaves: Delta, Theta, Alpha, Beta, and Gamma

1.1.3 Use of EEG for various clinical applications

The electroencephalogram, commonly referred to as EEG, is a method of neuroimaging that needs no invasive methods and looks at the electrical activity produced by the brain. Due to its capacity to provide useful insights into brain activity and diagnose a variety of neurological and psychiatric disorders, it has found widespread use in therapeutic settings [26], [27], [28], [29]. The following paragraphs talk about how EEG may be used for a variety of therapeutic purposes.

1. Diagnosis and Treatment of Epilepsy:
   The EEG is one of the key instruments used in the diagnosis and treatment of epilepsy, which is a neurological illness that is characterized by repeated seizures. Recordings of an EEG may capture epileptic activity such as aberrant

spikes, sharp waves, or rhythmic discharges, all of which aid in defining the seizure and verifying the diagnosis of epilepsy. Long-term EEG monitoring is especially helpful when it comes to recording elusive or uncommon seizure occurrences and determining how well therapy is working.

2. Sleep Disorders:

   The EEG is an important tool for the diagnosis and research of sleep disorders such as sleep apnea, narcolepsy, and insomnia. The phases of sleep may be categorized according to certain EEG patterns, such as the presence of delta waves in deep sleep or theta waves associated with rapid eye movement sleep. Sleep staging, which entails classifying distinct stages of sleep, is done based on these patterns. The EEG helps determine the structure of sleep, locate aberrant sleep patterns, and gauge the efficiency of various sleep therapies.

3. Evaluation of Patients Suffering from a Brain Injury or Who Are in a Coma:

   The EEG is a very useful tool for evaluating patients who have suffered a brain injury or who are in a coma. It helps identify the patient's degree of awareness, find aberrant brain activity, and forecast the prognosis of the patient's condition. Certain patterns on an EEG, such as burst suppression or widespread slowing, might help clinicians gain insight into the severity of a brain injury and make more informed treatment decisions.

4. Neurological Disorders:

   The EEG is used in the process of diagnosing and treating a wide variety of neurological disorders, such as stroke, multiple sclerosis, and movement disorders which can be Parkinson's disease. Patterns on an EEG may assist in differentiating between the various kinds of strokes and monitoring brain activity as the patient is recovering. Characteristic EEG abnormalities may often be seen in patients with movement disorders, which is helpful for both diagnosis and therapy planning.

5. Cognitive Function and Brain Mapping:

   EEG is used in cognitive neuroscience research to investigate brain activity during cognitive activities such as attention, memory, language processing, and decision-making. Researchers can explore cognitive processes and their underlying neural mechanisms by using ERPs, which are produced from EEGs and offer information on the brain's response to certain stimuli or events.

6. Psychiatric Disorders:

   The EEG has shown promise in the diagnosis and research of psychiatric disorders such as attention deficit hyperactivity disorder (ADHD), depression, and schizophrenia. The diagnosis, comprehension, and treatment of these conditions have all benefited from the discovery of distinctive EEG patterns or anomalies associated with the disorders. Neurofeedback methods that are based on EEG may also be utilized in some instances to control brain activity and reduce symptoms. EEG has become a potential instrument for the pre-emptive identification of stress and emotional disorders.

7. Pre-emptive identification of Stress and Emotional Disorders:

   EEG has become a capable method that goes for the proactive detection of stress and emotional disorders. Machine learning algorithms may be taught to categorize and forecast these disorders if certain EEG signals related to stress or emotional states are analyzed. The earlier a disease is detected, the more options there are for prompt treatments and individualized treatment strategies.

In conclusion, EEG is a flexible instrument that may be used in a broad variety of therapeutic settings. It is applied in the diagnosis, treatment, and research of conditions such as epilepsy, sleep disorders, brain injuries, neurological and psychiatric disorders, cognitive function, and the early identification of stress and emotional disorders. The EEG gives doctors and researchers significant insights into the activity of the brain, which enables them to better understand these illnesses, customize therapies, and enhance patient outcomes. The EEG continues to develop as a useful tool in clinical practice as a result of advances in signal processing and approaches for machine learning operations.

1.1.4 Models used to process EEG signals

Signals from an EEG are rather complicated and may provide insightful information about a person's brain function. Utilizing a broad range of models and techniques is required to extract meaningful insights from the processing and analysis of these data. [30]. In the following paragraphs, we will talk about some of the models that are often used to analyze EEG information sets [31], [32], [33].

i. Models for the Preprocessing Step:

The first phase in EEG signal analysis is called preprocessing, and its goal is to raise the signals' quality by eliminating undesired artifacts and noise and boosting their overall clarity. Several different preprocessing models are used, including the following:

• Filtering: EEG readings are often tainted by noise originating from a variety of sources, such as interference from power lines or muscle movement. Filtering strategies, such as bandpass filtering, high-pass filtering, and notch filtering, are used in a view to eliminate noise and isolate the frequency bands that are of interest.

• Artifact Removal: Eye blinks, muscle movements and electrode artifacts are all things that have the potential to impact EEG datasets & samples. To locate and eliminate these artifacts, prototypes like ICA and WT are used. This results in an improved quality of the EEG signal.

ii. Feature Extraction Models:

The method used to acquire pertinent data values detected from the EEG signals is referred to as feature extraction to define particular brain activities or situations [2]. These models are used to characterize specific brain activities or circumstances. To retrieve features, several models are used, including the following:

• Time-domain Features: Time-domain statistical measures including mean, variance, and skewness are retrieved from the EEG data. All those characteristics are referred to as "time-domain features." The amplitude, duration, and temporal properties of the signal may all be determined from the information provided by these features.

• Characteristics of the frequency domain EEG data are converted into the frequency domain by applying transformation models like as the Fourier transform and the wavelet transform, among others. When analyzing the distribution of energy across several frequency bands, the power spectral density, band power ratios, and peak frequencies may be retrieved.

• Time-Frequency Characteristics: Models like STFT or CWT are used to concurrently capture time and frequency information. Insights into the dynamic changes that occur in the EEG signal over time may be gained via the use of time-frequency characteristics such as spectrograms or wavelet scalograms.

iii. Classification Models:

Classification models are used in interest to classify EEG signals into various groups or situations based on the retrieved properties [6]. Models of categorization that are often used include:

• SVM: An established machine learning model is SVM that divides EEG signals into unique classes by using hyperplanes in a high-dimensional feature space. It is very useful when dealing with nonlinear classification issues because of its effectiveness.

• ANN: ANN models, such as feedforward or RNN, may be trained to categorize EEG data based on the properties that have been retrieved from those signals. These models can represent intricate relationships seen in the data and have shown encouraging results in a variety of EEG applications.

• Deep Learning Models: These modules include CNN or RNN with LSTM, viewed as getting a lot of interest in the realm of EEG data processing. These models are capable of autonomously learning hierarchical representations from raw EEG data, doing away with the need to manually extract features.

4. Statistical Models: This kind of model is useful in the process of analyzing EEG data and deriving relevant information about activity in the brain. The following are some examples of statistical models that are often used:

• Event-related Potentials (ERPs): ERPs are computed employing the average of a person's EEG responses to a certain stimulus or event. To determine whether or not the changes between circumstances are significant, ERP components are subjected to statistical examinations like t-tests and analysis of variance (ANOVA).

• Correlation Analysis: Correlation models, such as Pearson correlation or coherence analysis, are used in interest to investigate the connection that exists between EEG signals that were collected at various electrode positions. The functional connection patterns in the brain may be more easily identified with the aid of these models.

• Hidden Markov Models (HMM): HMMs are probabilistic models used to assess temporal relationships in EEG datasets & samples. They are especially helpful for modeling dynamic processes or locating hidden states within EEG datasets and samples, both of which may be found in the database[22].

To summarize, the processing of EEG data makes use of some different models, each of which fulfills a distinct function at a different level of the analysis. Classification models sort signals into categories, preprocessing models enhance signal quality, feature extraction methods retrieve pertinent information, and statistical models provide light on how the brain functions. The properties of the EEG data that are being examined as well as the particular purpose of the research or clinical study determine which models should be used for clinical use cases [34], [35]. Utilizing more sophisticated machine learning and deep learning models has made a substantial contribution to the development of EEG signal processing operations. This has made it possible to conduct an analysis of brain activity levels that is both more accurate and more efficient for real-time scenarios.

1.1.5 Clinical diseases identification process via EEG signals

EEG signals are very important in the process of identifying and diagnosing a wide variety of neurological disorders as well as clinical conditions. The examination of EEG data might give very helpful information on aberrant patterns of brain activity that are linked with certain illnesses [36], [37], [38]. This section of the text will go through the intricate process of diagnosing clinical disorders using EEG datasets and samples.

1. *Data gathering:*

   The process of identifying clinical disorders begins with the gathering of EEG datasets and samples, which is the first stage in the process. Electrodes are positioned on the scalp in interest to capture EEG datasets & samples. These electrodes detect the electrical activity that is produced by the brain. The precise recording procedure and the particular brain areas of interest both have a role in determining the electrodes' locations as well as their overall quantity used. Amplification, digitization, and storage of the recorded signals are done in preparation for subsequent investigation[39].

2. ***Preprocessing:***

   After the EEG data have been gathered, the next step is to apply the preprocessing techniques in an effort to raise the signals' quality and get rid of any artifacts or noise that can get in the way of the analysis. Preprocessing methods include:

   • Filtering: The noise in the EEG data is removed by filtering, which also helps to separate the frequency bands of interest. Bandpass filters, high-pass filters, and notch filters are some of the most common types of filters [40].

   • Artifact Removal: Eye blinks, muscle movements or electrode artifacts may contaminate EEG results. In interest to locate and eliminate these artifacts, methods such as ICA and wavelet transform are used [41].

3. ***Feature Extraction:***

   The purpose of feature extraction is to get pertinent information from the preprocessed EEG data in interest to differentiate between various clinical conditions. From the EEG waves, a variety of characteristics are retrieved, including the following:

• Time-Domain properties: Insights into the amplitude and temporal properties of the EEG signals may be gained by the use of statistical measures such as the mean, variance, or peak amplitude [42].

• Characteristics Obtained from the Frequency Domain: like power spectral density, band power ratios, or dominant frequency, reflect the distribution of energy over many distinct frequency bands [43].

• Timing and Frequency Characteristics: The extraction of time-frequency representations, such as spectrograms or wavelet scalograms, which capture both temporal and spectral variations in the EEG signals is made possible by techniques such as STFT or WT [44].

4. ***Classification and Diagnosis:***

After the relevant characteristics have been retrieved, classification models are used to categorize the EEG signals into various clinical illness categories. This step is followed by the diagnosis step. For classification purposes, machine learning methods such as SVM, ANN, and deep learning models are often used. These models are trained using labeled datasets, in which the EEG signals are linked to various illness classifications. During the phase of classification, the models make a diagnosis based on the extracted properties of the input EEG data to determine which illness group it belongs to.

5. ***Validation and Performance Evaluation:***

The categorization models' performance in this phase is examined to see how accurate and reliable they are in diagnosing clinical disorders. This may be accomplished by testing the models on separate datasets or via means of cross-validation methods. One way to assess the effectiveness of the categorization models is by using performance metrics such as accuracy, sensitivity, specificity, and precision, as well as ROC curve analysis.

6. ***Clinical Interpretation:***

   This is the sixth and last phase in the procedure, and it includes the clinical interpretation of the categorization findings. The illness categories that have been established have the potential to give helpful insights into the neurological status of the patient. Neurologists and other medical experts analyze the categorization results and utilize them as a supporting source of information for the purposes of diagnosis, treatment planning, and monitoring the development of the condition.

It is essential to keep in mind that the diagnosis of clinical conditions using EEG signals is an arduous undertaking in which physicians and researchers must collaborate who are knowledgeable in their respective fields. Research in this field is continuing, with the overarching goal of enhancing illness diagnosis, facilitating early detection, and improving patient care in a variety of clinical settings via the creation of accurate and reliable classification models [45], [46], [47].

In conclusion, the process of diagnosing clinical disorders using EEG signals encompasses data gathering, preprocessing, feature extraction, classification, validation, and clinical interpretation of the results. Extracting useful information from EEG signals and assisting in the diagnosis and treatment of neurological disorders may be accomplished with the help of this multi-stage procedure, which employs advanced signal processing techniques and machine learning algorithms.

1.1.6 Brief review of disease identification models

Numerous models for identifying diseases have been developed recently to assist in the diagnosis and monitoring of neurological disorders by analyzing EEG datasets & samples. These models have been developed to evaluate EEG signals. Complex ML and DL techniques are employed by these models to extract useful characteristics within EEG data and reliably categorize them into a variety of disease categories [48], [49], [50]. This area offers a concise overview of a variety of well-known disease detection models.

1. ***CNN:***

   Based on EEG measurements, CNN models have been widely employed for disease diagnosis. Convolutional layers are used in these models so that the models may automatically learn hierarchical features based on the input signals. CNNs have exhibited outstanding execution across a range of jobs, including the detection of seizures, the categorization of Alzheimer's disease, and the identification of sleep stages. Their ability to identify patterns in the EEG data, both local and global, allows them to precisely categorize illnesses. [51] [52] [53] [54] [55] [56].

2. ***RNN:***

   RNNs are appropriate for EEG signal analysis because they are especially good at identifying temporal relationships and sequential patterns in time-series datasets & samples. The RNN variations known as LSTM and GRU are becoming more used in disease diagnosis models. In a range of applications, including the detection of emotions, the diagnosis of epilepsy, and the creation of brain-computer interface systems, RNNs have demonstrated positive results [57] [58] [59] [60].

3. ***SVM:***

   A well-liked machine learning technique called SVM is utilized to diagnose diseases based on EEG readings. The goal of SVM models is to locate an ideal hyperplane in a high-dimensional feature space that can differentiate between various disease classifications. SVMs have been effectively used in a variety of applications, including the categorization of epilepsy, motor imagery-based brain-computer interfaces, and the detection of Alzheimer's disease [61] [62] [63] [64].

4. ***DBN:***

   DBNs are generative models that develop hierarchical representations of datasets and samples by combining many layers of restricted Boltzmann machines (RBMs). They have been used in the diagnosis of diseases based on EEGs, such as the detection of epilepsy and the categorization of different stages of sleep. DBNs have shown promising performance in a variety of clinical applications and have the ability to automatically extract important characteristics from EEG datasets & samples [65] [66] [67] [68] [69].

5. ***Ensemble Models:***

   Ensemble models are a way to increase overall disease detection performance by combining numerous separate classifiers into a single model. The creation of trustworthy and precise ensemble models for EEG signal processing has involved the application of techniques like bagging, boosting, and stacking, amongst others. Ensemble models have been applied in numerous contexts including motor imagery-based brain-computer interfaces, emotion identification, and the categorization of sleep stages [70] [71] [72] [73] [74] [75].

6. ***Transfer Learning:***

   Within the field of EEG-based disease detection, transfer learning techniques have gained prominence recently. Transfer learning enables the application of information gained in one domain (for example, a dataset that has been well labeled) to another domain (the target domain) that has less labeled datasets and samples. Transfer learning improves the performance of disease detection models using smaller datasets by making use of previously trained models that have been run on large-scale datasets. This technique has demonstrated promise for application in the diagnosis of cognitive impairment, the identification of epilepsy, and the procedure for recognizing emotions [76] [77] [78] [79].

It is essential to keep in mind that the performance and applicability of disease identification models change depending on the nature of the disease in question, the features of the dataset, and the experimental configurations used. The choice of an acceptable model is determined by many considerations, including the characteristics of the disease, the data that are at hand, the amount of computing that is necessary, and the degrees of interpretability that are sought [80] [81].

In conclusion, disease identification models based on CNNs, RNNs, SVMs, DBNs, ensemble methods, and Transfer learning have demonstrated a great deal of promise for precisely identifying EEG signals for various neurological disorders. The continuation of research and development efforts in this area holds a great deal of potential for enhancing the precision, clinical value, and operational cost-effectiveness of disease identification models in the foreseeable future scenarios.

1.2 MOTIVATION OF THIS WORK

Because of the enormous influence that stress and emotional disorders have on the overall quality of life and the well-being of persons, the motivation for doing this study on efficient EEG categorization for the preemptive diagnosis of stress and emotional disorders arises from this impact. In today's world, stress and disorders caused by emotions such as depression, anxiety, and PTSD are all too common [82]. If these problems are not handled, they may have serious psychological and physiological repercussions if they are allowed to go unchecked. In interest to effectively treat and manage these disorders, early identification and intervention are both very necessary components.

The traditional techniques of diagnosing emotional disorders and stress depend mainly on subjective evaluations, self-reporting, and clinical interviews. These procedures may be time-consuming, expensive, and prone to biases. Signals from an EEG provide a one-of-a-kind chance to objectively measure and examine brain activity. As a result, this kind of investigation yields vital insights into the neurological causes of various disorders. EEG signals may be utilized as biomarkers to correctly diagnose and categorize a variety of emotional and stress-related disorders [83] [84] [85]. Because of the latest advancements in machine learning and signal processing techniques, this is feasible.

The formation of effective EEG classification models for the early diagnosis of emotional disorders and stress is driven by many different variables, including the following:

1. Early Intervention: The early discovery of stress and emotional disorders allows immediate intervention, which may avoid the worsening of symptoms and enhance treatment results. Early detection of stress and emotional disorders enables timely intervention[86]. It is now feasible to intervene in the course of several disorders before they reach more severe phases, thanks to the discovery of unique EEG patterns that are connected with each condition.

2. Personalized Treatment: Classification models based on EEG data may be used to help in the process of customizing treatment plans for particular patients. By gaining an awareness of the distinct EEG signatures associated with various disorders, it is possible to build individualized treatment strategies that take into consideration the particular neurological deregulations that are shown by each patient.

3. Objective Assessment By reducing the dependence on subjective judgments and increasing the accuracy and reliability of diagnosis, objective measurements, which are supplied by EEG signals, are used. This objective evaluation is especially helpful in situations in which patients may have difficulties articulating their emotional experiences or in which patients' reports may not be credible.

4. EEG is a neuroimaging method that is non-invasive and generally low-cost in contrast to alternative methods viewed in fMRI and positron emission tomography (PET) [87] [88]. Because of its accessibility, EEG is a practical instrument that may be used for mass screening and monitoring of emotional disorders and stress.

5. Monitoring in real-time EEG data may be recorded in real-time, which enables continuous monitoring of brain activity during a variety of tasks, stimuli, or activities that are part of everyday life. Real-time monitoring allows the detection of instantaneous alterations in brain activity brought on by emotional or stressful situations, offering vital insights into the dynamics of these disorders. Real-time monitoring enables the detection of immediate variations in brain activity brought on by stressors or emotionally charged situations [89] [90] [91].

Aim seeks to contribute to the progress of therapeutic procedures linked to stress and emotional disorders by building effective EEG classification models. These models will be used in clinical settings. The models that have been developed may provide physicians and researchers with assistance in making accurate diagnoses, creating individualized treatments, and evaluating the efficacy of interventions. In addition, these models have the potential to be integrated into wearable devices or mobile apps, which would make it possible for people to self-monitor their brain activity and proactively manage their stress and emotional well-being in response to a variety of events.

The overarching aspiration of this line of research was to use the power of EEG signals and sophisticated data processing tools to develop a method that is objective, effective, and preventative in the diagnosis of emotional disorders and stress-related conditions. The aim is to have a significant effect on the lives of those who are afflicted by these disorders by strengthening early detection methods as well as individualized treatment techniques. The ultimate objective is to raise these people's general quality of life and well-being.

1.3 PROBLEM STATEMENT

The subject that is investigated in this thesis is the need for effective EEG classification algorithms that can be used in interest to facilitate the prompt detection of emotional disorders and stress. The psychological well-being and well-being of humans may be significantly impacted by factors such as stress and emotional disorders including anxiety, depression, and post-traumatic stress disorder (PTSD). In interest to effectively treat and manage these disorders, early identification and intervention are both very necessary components. However, conventional methods of diagnosis mainly depend on self-reporting and subjective judgments, both of which may be time-consuming, are prone to biases, and may not offer findings that are objective and reliable for clinical scenarios.

EEG data provide a potentially useful path toward the objective diagnosis and categorization of emotional disorders and states of stress. Signals from an EEG may shed light on the electrical activity caused by the brain and reflect the underlying neurological processes that are related to a variety of mental states and disorders. It is possible to find certain patterns and biomarkers that are symptomatic of a variety of emotional disorders and stress-related conditions by performing an analysis and interpretation of EEG datasets & samples. On the other hand, a precise and effective categorization of EEG data presents many issues that need to be tackled.

To begin, EEG impulses are naturally complicated and noisy, which makes it difficult to get useful information from them. EEG recordings are susceptible to contamination from a wide variety of artifacts, including eye blinks, muscular activity, and external interference, all of which may result in a reduction in classification accuracy. In interest to raise the EEG signals' quality as well as their interpretability, preprocessing methods such as artifact removal, noise reduction, and feature extraction need to be developed.

Second, the categorization of EEG data needs the creation of machine learning models that are both reliable and effective. Because EEG datasets and samples are both high-dimensional and temporal, it's possible that traditional classification methods won't be enough to work with them. In an interest to properly interpret and categorize EEG data, novel machine learning methods such as deep learning architectures, ensemble models, or transfer learning approaches need to be researched and adapted.

In addition to this, the categorization models need to be adaptable enough to deal with numerous forms of stress as well as emotional disorders at the same time. It might be difficult to effectively discern between various disorders since they may display overlapping EEG patterns or have comparable underlying brain pathways. This can make it difficult to diagnose. The classification models need to be able to offer findings that are dependable and easy to comprehend, as well as reflect the nuances of difference that exist amongst various disorders.

In addition, the suggested categorization models have to be usable in clinical environments that take place in the real world. They have to have a high level of computing efficiency and be able to handle massive volumes of data in a reasonable length of time. In addition to this, the models need to be interpretable so that physicians may get an understanding of the underlying neurological processes that are contributing to the classification findings. The end objective is to build a useful tool that may aid physicians in early identification, tailored treatment planning, and tracking the development of stress and emotional disorders.

In conclusion, the purpose is to investigate the topic of developing effective EEG classification algorithms for the early diagnosis of emotional disorders and stress. This requires resolving issues that arise during the preprocessing of EEG data, developing reliable ML models, managing several disorders at the same time, and guaranteeing that the solution can be used in real-world clinical situations. This seeks to equip doctors with reliable and objective strategies for early identification and action, to ultimately improve the overall well-being and quality of life for those who are impacted by stress and emotional disorders. This will be accomplished by addressing these issues.

1.4 FUNDAMENTAL GOALS

The fundamental goal is to create effective EEG classification approaches for the early diagnosis of emotional disorders and stress-related conditions. These broad aims may be broken down even further into the following particular objectives:

1. Investigate and evaluate currently used EEG processing techniques. The first goal is to carry out a thorough assessment and analysis of the already used EEG processing methods. This entails researching the many preprocessing approaches, feature extraction strategies, and classification algorithms that are used in the relevant published literature. By analyzing the benefits and drawbacks of different methodologies, one may provide a strong groundwork for the creation of innovative and enhanced research strategies.

2. Conceive and put into practice advanced preprocessing methods. The second goal is to conceive of and put into practice advanced preprocessing techniques to raise the EEG signals' level of quality and their interpretability. In interest to do this, there’s a need to solve difficulties such as artifact removal, noise reduction, and feature extraction. There will be an investigation of the use of cutting-edge techniques for the identification and elimination of artifacts, such as ICA and adaptive filtering. In addition, methodologies for the extraction of features from EEG signals that capture significant information, such as time-domain type, frequency-domain type, and time-frequency type analysis, will be researched and put into practice.

3. Create and implement innovative machine learning models especially geared toward the arrangement of EEG signals. The third intent is to produce and implement innovative ML models specifically geared toward the classification of EEG signals. The temporal structure and high-dimensional properties of EEG datasets and samples may not be completely exploited by conventional classification techniques such as SVM or RF. In interest to effectively handle EEG classification tasks, therefore, advanced techniques such as deep learning architectures, ensemble models, or transfer learning approaches will be explored and customized. These models will be capable of learning complex patterns and extracting discriminative features from EEG signals, which will lead to accurate and reliable classification results.

4. Using datasets from real-world applications evaluate the developed EEG classification models. The fourth goal is to evaluate the effectiveness of the generated EEG classification models using real-world datasets. These databases need to include a broad spectrum of stress and emotional disorders, such as anxiety, depression, PTSD, and a variety of others. On these datasets, the models will be trained, verified, and tested in interest to evaluate the classification accuracy, precision, and recall, as well as any other performance metrics they may have. In interest to show that the suggested models are more effective than the state-of-the-art methodologies that are already in use, a comparison study will be carried out.

5. Give some insight into the interpretability of the classification findings. The fifth goal is to make sure that the classification results that were produced by the constructed models are interpretable. Clinical decision-making needs to have a solid understanding of the neurological processes and biomarkers that contribute to the categorization results. In interested giving insights into the areas or patterns within the EEG signals that contribute the most to the classification findings. Clinicians will benefit from this since it will make it easier for them to comprehend and make use of the categorization results.

6. Validate the suggested models in a clinical context. The sixth and last goal is to validate the created EEG classification models in a clinical environment that is representative of the real world. In the interest of testing the models on patient data and collecting feedback on their usability, accuracy, and clinical relevance, there is a need to form collaborations with healthcare professionals and academics working in the area. Evaluations will be done to determine how well the models perform in terms of real-time processing, scalability, and simplicity of integration into pre-existing clinical processes.

The main objective is to contribute to the area of EEG-based preemptive identification of stress and emotional disorders. This will be accomplished by completing the goals listed above. The methodologies and models that have been developed possess the capacity to raise the accuracy, efficiency, and clinical application of EEG categorization, which will eventually facilitate the early identification, tailored treatment, and better management of stress and emotional disorders, leading to improved patient outcomes.

1.5 OBJECTIVES

1. To review and analyse the existing techniques and algorithms for stress recognition and emotion detection.

2. To propose the novel feature extraction algorithm using suitable channels and bands for human stress recognition & emotion detection.

3. To develop and implement an automated stress recognition & emotion detection system.

4. To compare and evaluate the proposed work with existing methodologies.

1.6 THESIS ORGANIZATION

The flow of the thesis is arranged logically, beginning with a general introduction to EEG processing and progressively diving into particular components, applications, and models utilized in the area. The thesis also begins with a general introduction to EEG processing and ends with a conclusion. The identification of diseases employing EEG signals is the primary emphasis of this thesis, which also makes unique suggestions for methods of categorization and detection process.

Chapter 1 presents an introduction to EEG Processing. This chapter provides a fundamental knowledge of the topic by introducing the idea of EEG processing and presenting examples of its use. The fundamentals of EEG signals, their collection, and the importance of EEG in clinical applications are all covered in this section. Different aspects of EEG signal composition, Utilization of EEG in some different therapeutic contexts, Models that are employed in the processing of EEG data, the technique of diagnosing clinical disorders using EEG data, a quick look at the various disease identification models, and the impetus for this study is being discussed in this chapter. Also covering the motivation of the work, problem statement, objectives, and covering flow of the thesis at the end.

Chapter 2 covers the Literature review of this study. The Empirical analysis, model design, result analysis, and conclusions are covered. These chapters make up the meat and potatoes of the thesis; they are the parts that provide and analyze the many recommended models and techniques. An empirical analysis of existing EEG processing techniques is presented in this chapter.

Chapter 3 covers the layout of a multispectral data representation engine for the classification of EEG signals using ensemble models including the introduction, Existing models that perform multispectral data representation analysis, and the design part.

Chapter 4 covers the layout of a Transfer Learning-based Bioinspired Ensemble Model for Preemptive Detection of Stress and Emotional Disorders is the main topic. Following the examination and comparison of the results in each chapter are the respective conclusions.

Chapter 5 covers the result and discussion of the Multispectral Data Representation Engine for the Classification of EEG Signals passing through Ensemble Models and Transfer Learning Based Bioinspired Ensemble Model for Preemptive Detection of Stress & Emotional Disorders.

Chapter 6 covers conclusions and prospects for the Future. The findings and interpretations of the study presented in the thesis are summarized in the concluding chapter. In it, the most important results, contributions, and limits are summed up. In addition to this, it explores potential avenues for future study and expansion in the part of EEG processing and disease diagnosis.

The structure of the thesis as a whole is organized to facilitate the development of a thorough knowledge of EEG processing, the diagnosis of disease, and the proposal of creative models for analysis. It moves from the underlying principles to the suggested solutions and their assessments in a logical progression, finally leading to conclusions and potential possibilities for further study for different scenarios.

CHAPTER 2

LITERATURE REVIEW

"The greatest challenge to any thinker is stating the problem in a way that will allow a solution."

- Bertrand Russell

The burgeoning interest in EEG stems from its non-invasive nature and high temporal resolution, making it indispensable in both clinical and research settings. This review aims to provide a comprehensive overview of these techniques, emphasizing empirical studies that have rigorously assessed their performance. By critically evaluating existing literature, this work seeks to identify gaps, challenges, and emerging trends in EEG signal processing. Furthermore, it aims to delineate benchmarks and best practices that can guide future research and clinical applications.

2.1 EMPIRICAL ANALYSIS OF EXISTING EEG PROCESSING TECHNIQUES

Jianhai Zhang et.al 2016 [92] conducted a study on the identification of emotions from EEG signals, a topic garnering significant interest due to advancements in wearable technology and the demand for more immersive human-computer interfaces. Their study aimed to demonstrate the effectiveness of their proposed methods, comparing them with similar strategies based on the F-score metric. Their experiments revealed that evaluating channels as a unified entity resulted in better performance in reducing the number of channels while maintaining acceptable accuracy levels. Specifically, by adjusting the channel weights according to how well they contribute to precision in classification, they were able to reduce and contrast using all 19 channels, the number of channels to eight with only a modest drop in accuracy.

Abeer Al-Nafjan et.al 2017 [93] examined the trends in research on EEG-based emotion recognition systems. Of the 285 publications they analyzed, 160 were from academic journals that have been published since the inception of emotional computing research. Their findings indicated a growing interest among researchers in utilizing EEG technology for emotion recognition. This tendency was influenced by some variables, such as the accessibility of wireless EEG equipment, developments in computational intelligence methods, and the application of machine learning algorithms.

Xin Chai et.al 2017 [94] suggested a novel technique to solve the problem of combining marginal and conditional distributions in emotion recognition from EEG data: adaptive subspace feature matching (ASFM). The goal of this technique is to match the EEG data distributions from a source domain to a target domain. The disparities between the source and target domains' marginal and conditional distributions are lessened as a result of this alignment procedure. As a result, LR can be applied to the aligned source domain to train a classifier for use in the target domain, as the distribution of the aligned source domain becomes similar to that of the target domain. The authors used a public EEG dataset with three affective states—positive, neutral, and negative to compare their ASFM method with six other methods. They carried out assessments both online and offline. The findings of the offline trial demonstrated that ASFM outperformed the state-of-the-art technique, the subspace alignment auto-encoder (SAAE), in terms of mean accuracy.

Xiang Li et.al 2018 [95] proposed a novel approach for processing neurophysiological signals to recognize emotions. They presented a preprocessing method that uses scalograms and wavelet transforms to arrange these signals into frames that resemble grids. They also created a hybrid deep learning model that combines the architectures of RNN and CNN. This model aims to extract relevant features for the task, uncover inter-channel correlations within the signals, and incorporate contextual information from the frames. To validate their approach, they conducted experiments on the DEAP benchmarking dataset, focusing on trial-level emotion recognition. Their findings highlighted the effectiveness of their methods, particularly in accurately identifying emotional dimensions such as Valence and Arousal.

Barjinder Kaur et.al 2018 [96] investigated how emotions, both positive and negative, impact human behavior using a method called affective computing. In interest to carry out their study, they had ten participants watch different video clips meant to evoke different emotions while their EEG signals were being recorded in real-time. The EEG signals were then processed to extract a feature known as fractal dimension. The researchers used the RBF kernel in their SVM classification algorithm to figure out emotional states using this extracted feature. The results showed that emotions could indeed be recognized from EEG signals, with an average accuracy of 60%.

Mi Li et. Al 2018 [95] aimed to figure out the way various frequency bands and various amounts of EEG channels affected the precision of emotion identification from EEG signals. The DWT was applied to divide the EEG signals into four bands of frequency after the DEAP dataset had been calibrated. Features such as entropy and energy were calculated from these bands and used in conjunction with the KNN classifier for classification. The results indicated that the classification accuracies varied depending on the number of EEG channels and the frequency band used. They also emphasized that the beta, alpha, and theta frequency ranges were of interest to yield the highest classification accuracy levels, with the gamma frequency band bending the highest results.

J. X. CHEN et.al 2019 [97] implied a methodology leverages end-to-end automatic learning that could enhance the precise amount of recognizing emotions from EEG data. They proposed a method based on deep CNNs to automatically extract emotional features from EEG signals in both spatial and temporal dimensions. They exploited the DEAP dataset's EEG signals to retrieve temporal characteristics, frequential characteristics, and combinations of these characteristics. For binary emotional classification in both valence and arousal dimensions, they compared the effectiveness of deep CNN models with shallow machine learning models like BT, SVM, LDA, and Bayesian LDA. Specifically, when using combined temporal and frequency features, the valence and arousal dimensions of the deep CNN models performed 3.58% and 3.29% more appealing as compared to the best standard BT classifier.

Hao-Yan Chang et al.2020 [98] identified the components that regulate how well BCI functions while utilizing an SSVEP-based BCI which is integrated into a game with a purpose (GWAP). The purpose of this research was to collect data over extended periods, simultaneously in high- and low-stress scenarios. The researchers utilized a statistical technique called Canonical Correlation Analysis (CCA) was a tool to judge if players were able to find and concentrate on the appropriate target while playing the game. Time's repercussions for search accuracy and impact of time stress on SSVEP accuracy in which average accuracy in low-stress conditions was quite high at 98.6%, and accuracy approached 100% when the participants took more than three seconds to find the target. In high-stress scenarios, the SSVEP's grand average accuracy fell dramatically to 82.1% from 98.1%. Accuracy observed in low-stress conditions

Po-Yuan Jeng et al.2020 [99] presented a low-dimensional representation of the data obtained from aspects during pre-trial EEG recordings which serves as an organizing principle for a transfer learning framework for EEG decoding. Researchers make use of existing EEG data from different users and only a small amount of data from a new user to create an accurate BCI. They tested their proposed method and adopted a LOSO cross-validation strategy as well, contrasted the outcomes with the most recent investigations in the field, and baseline performance. The key finding of their research is that their proposed method outperformed the random selection (baseline) in all scenarios they tested (indicated by $p < 0.05$), which implies that their approach can significantly improve performance in most situations. The suggested plan of action achieved an additional 17% prediction performance surpassing the baseline for random selection for transferring eight sessions of data. Their method performed substantially better despite fewer training data (again, $p < 0.05$) than the Riemannian manifold method when selecting eight or nine sessions.

Zhe Sun et al.2020 [100] investigated the neural network's performance called WLnet which can accurately detect mental workload levels, both in stressful and non-stressful situations. To evaluate the performance of WLnet, the researchers conducted tests using four different methods: CSP, TCSGSP, EEGNet, and WLnet itself. The researchers carried out the cross-entropy loss function in the Adam algorithm to optimize the neural networks. The results showed that all three models (CSP, TCSGSP, EEGNet) performed better as opposed to cross-context tasks, in within-context tasks. This suggests the emotional or affective context plays a significant role in influencing mental workload levels, leading to differences in data distribution between the two contexts.

Jung-Tai King et al.2020 [101] investigated two virtual driving scenarios aimed at assessing response inhibition abilities and manipulating time limitation in one of these scenarios to induce stress, effectively making it more challenging. The primary focus of their study was on stop signal task (SST), which is a paradigm used to study response inhibition. To discover more regarding the neural mechanisms underpinning the inhibition and go tasks, the researchers applied an analysis called Event-Related Spectral Perturbation (ERSP) to study EEG activity in the frequency domain. Specifically, the Stop-Task (SST) showed boosted theta and delta power following the initial triggering of the stop signal compared to unsuccessful stop trials (USSTs). The findings highlighted the central brain region's beta (β) and gamma (γ) scores which prove to be noteworthy, particularly in high-pressure emergency driving scenarios.

Ekansh Sareen et al. 2020 [102] conducted a study focusing on individuals with Intellectual and Developmental Disorders (IDD). The study aimed to uncover specific characteristics of the IDD group's brain networks and to investigate the effects of soothing music on these networks. They also compared the response of typically developing control (TDC) subjects to soothing music which includes participants involved seven individuals with IDD and seven typically developing control subjects (TDC the researchers collected raw EEG data using an Emotive EPOC 14-channel wireless EEG headset. The IDD group showed higher functional brain interaction in the beta, gamma, theta, and alpha bands compared to the TDC group during both resting and music-listening states. The TDC group exhibited higher functional brain connectivity with little context to the IDD group in the resting and listening phases. The IDD group showed more modular clusters in the gamma and beta bands, suggesting a more organized and efficient brain network during music listening. The TDC group demonstrated differences in brain connectivity during music listening, indicating a unique response to music stimuli.

Sung-Woo Kim et al. 2020 [103] proposed a multi-biosignal wearable wireless interface intended for sleep analysis. This innovative device allows for comfortable sleep monitoring with the added capability of directly classifying sleep stages, which sets it apart from conventional sleep analysis tools like Polysomnography (PSG). Their device employs four internal readout channels that are deployed by the Readout Integrated Circuit (ROIC) to acquire these bio-potential signals. The ROIC includes an analog feature extraction circuit which means that the device can automatically determine which sleep stage a person is in without the need for extensive post-analysis or expert interpretation. They've integrated three circuits for extracting features for EEG, EMG, and EOG data within the ROIC. These features are used to estimate sleep stages directly by utilizing a decision tree algorithm. This classification happens in real-time, allowing for continuous monitoring of a person's sleep stages. Their study demonstrated promising results, achieving a classification correlation of 74% for sleep stages.

Haiyun Huang et.al 2021 [104] developed an EEG-based BCI system for recognizing emotions. In their study, they presented video clips representing positive and negative emotions to participants while simultaneously collecting and processing EEG data. The experiment involved ten healthy subjects, and the system achieved a high average online accuracy of 91.5% with a small standard deviation of 6.34%. This indicated that the system effectively evoked and recognized the emotions of the participants. The researchers also explored the clinical application of their BCI system for individuals struggling with disorders of consciousness (DOC), like vegetative state or coma, who often have difficulty expressing emotions verbally or through physical movements. The results indicate that the postulated BCI system may be an effective tool to gauge the emotional states of DOC patients.

Yang Li, et al. 2021 [105] proposed two neural network models, BiDANN and the improved BiDANN-S. These models were developed to recognize emotions from EEG data. BiDANN-S was specifically designed to make emotion recognition from EEG data less influenced by the unique characteristics of individual subjects which helps the model work well across different people. BiDANN-S performed better than a range of other methods when applied to EEG-based emotion recognition. These methods included KLIEP, ULSIF, STM, linear SVM, KPCA, TCA, TKL, SA, GFK, T-SVM, TPT, and DGCNN. In particular, BiDANN-S achieved an accuracy rate of 63.01% in the δ frequency band and 73.72% in the γ frequency band. These results demonstrate that BiDANN-S significantly improved emotion recognition in EEG data, especially in these specific frequency bands.

Fatih Demir, et al. 2021 [106] researchers investigated and explored an advanced method for automatically categorizing people's emotional states. The study introduced a hybrid method that combined CWT-based EEG signal processing with cutting-edge CNN models for stealing deep features. This approach achieved remarkable accuracy in categorizing a wide range of emotional states, surpassing the performance of previously employed methods in the field of EEG-based emotional classification. They used the CWT to extract rhythmic signals from EEG data and then transformed these signals into visual EEG rhythm images. Due to high accuracy rates of 90.6% hybrid approach stands out as one of the most effective approaches for accurately employing EEG data for categorizing emotions.

Zhe Wang, et al. 2021 [107] adopted an entirely novel deep learning framework deemed as the frame-level distilling neural network (FLDNet), which is beneficial in predicting emotions since it can extract significant features from correlations between many frames. They compared FLDNet with several other deep learning-based algorithms such as DNN, CNN, LSTM, CLSTM, attention-LSTM, RACNN, and ATDDLSTM to evaluate its performance. For DEAP, FLDNet achieved high accuracy rates for valence (83.85%), arousal (78.2%), and dominance (77.52%), surpassing all competing methods. Similarly, on the DREAMER datasets, FLDNet achieved average recognition accuracies of 89.91% for valence, 87.67% for arousal, and 90.28% for dominance, again outperforming other methods.

Eyad Talal Attar et al. 2021 [108] explored a comprehensive approach to understanding and analyzing stress. They focused on delving into the relationship between heart rate variability (HRV) and EEG under stress conditions providing complementary information that can enhance understanding of stress. To induce stress in their subjects, they used a well-known Stroop Color-Word Test (SCWT), a neuropsychological evaluation measuring tool. This test is useful for measuring cognitive processing and provides valuable insights into brain function. The study revealed correlations between HRV features, such as rMSSD (root mean square of successive differences), LF/HF ratio, HF (high frequency), and LF (low frequency) with EEG traits, particularly the left hemisphere's alpha power band and alpha band power asymmetry. Their research identified five noteworthy connections between stress-related HRV characteristics and EEG.

Jung Hwan Kim et al.2021 [109] experimented using a deep learning system based on EEG to evaluate the fatigue-induced drowsiness (FFD) of an operator. This experiment aimed to understand the patterns in EEG data when individuals perform cognitive activities prior to accessing the main control room (MCR) for safe nuclear reactor operations. They chose to design an Integrated Safety Management System (ISMS) that incorporates CNN and LSTM as ISMS can rapidly and securely process information related to results from FFD and PI used for scheduling daily tasks. For each of the 100 datasets, the researchers determined the average amount of time needed for pseudonymization, authenticated encryption, and decryption. Pseudonymization was executed via the SHA-256 hash function, while authenticated encryption and decryption were accomplished using the AES-256 algorithm and the

EAX mode. AES encryption is known for its ability to securely decrypt data without keys and accommodates 128, 192, or 256-bit key widths.

Ibrahim L. Olokodana et al. 2021 [110] and the team successfully applied Kriging methods to create an efficient seizure detection device, specifically designed for the context of edge computing by contemplating the brain as a spatial area. The research was to develop a wearable device capable of instinctual detection of seizures in real-time utilizing EEG signals. To achieve this, they employed three different kinds of Kriging approaches: Universal, Ordinary, and Simple. The researchers evaluated the reliability of their technique for detecting seizures by comparing the three different Kriging methods. Simple and Ordinary Kriging demonstrated corresponding outcomes, achieving high confidence intervals of 99.7% and 95.4%, respectively. Simple Kriging outperformed Ordinary Kriging when considering a confidence interval of 68.2%.

Cezary Sielu˙zycki et al. 2021 [111] focused on experimental paradigms using magnetoencephalography (MEG) and EEG to estimate brain-evoked responses. They introduced a novel approach called a "bootstrap framework" to substantially reduce the amount of assessments carried out for performing tests necessary for these experiments, particularly those emphasizing brain-evoked reviews. Despite the availability of various alternative models, the researchers chose to stick with the classical SPN (single-process neural) model. This model is widely used across a broad spectrum of experimental paradigms. The primary objective of their study was to develop a methodical framework that would enable the least number of stimulus repeats in MEG/EEG research. Reducing the number of repetitions minimizes the time burden on study subjects, thereby decreasing potential artifacts caused by factors such as tense muscles, jerky head motions, blinked eyes, and an intense alpha rhythm from fatigue.

Abdelghafar R. Elshenaway et al.2021 [112] researchers developed a novel technique for Internet of Things (IoT) device authentication based on hand gestures and EEG signals. They utilized an affordable NeuroSky MindWave headset to determine malleable meditation and concentration thresholds that act as the authentication key. To assess the viability of this method three key criteria were taken into consideration: usability, security, and authentication time. To evaluate usability, researchers conducted user testing to gauge the adaptability of participants through EEG signals and hand gestures for authentication. Security is vital to ensure that unauthorized access is prevented. Authentication time refers to user authentication in which the average authentication time for their prototype was 33 seconds, which was considered acceptable only if the method was based on selecting four adaptive threshold bits related to attention and meditation within that time frame. The proposed method is promising and compares favorably to existing BCI-based studies in terms of efficiency.

Charalampos Saitis et al.2021 [113] introduced a novel approach that utilizes a multifaceted framework to focus on the particular urban environment that people are applying for random forest classifiers. They achieved this by monitoring real-time, non-invasive, and ambulatory brain and peripheral biosignals. The goal was to understand how people's brains and bodies react to different urban settings. With an accuracy of 93% for outdoor situations and 87% for inside environments, the model performed admirably. The fusion models combined different types of data (EEG, EDA, BVP) and identified the most predictive features for environment classification EDA (electrodermal activity) and HR (heart rate) signals recorded by the Empatica E4 wristband Research presented an approach for evaluating visual impaired people's cognitive and emotional experiences in real-time as they maneuver various environments both inside and out. Robust multimodal classification trials and good prediction rates indicated a commitment to upgrading life quality in visually impaired individuals.

Mahima Ma Weerasinghe et al. 2021 [114] conducted research focused on Spiking Neural Networks (SNNs) and the significance of methodically choosing the number of hidden layer neurons, particularly when learning with Spike Time Dependent

Plasticity (STDP). They aimed to develop learning algorithms for SNNs and demonstrate the potential applications of SNNs in processing spatiotemporal data, particularly EEG data with its temporal properties such as autocorrelation and heterogeneity. For an assignment involving three classes in the Wrist Flexion dataset, using an SNN with 111 hidden neurons, they achieved an average classification accuracy of approximately 94%. In a 2-class classification task for utilizing the Emotional Stress dataset for differentiation between stressed and composed brain states, using SNN as 130 hidden layer neurons yielded an average classification accuracy of about 92%. They also applied Spike Propagation (SP) for mental state recognition, achieving accuracy rates of 76.86% for arousal and 73.1% for valence classification under 10-fold cross-validation.

Yang Li et al.2021 [115] investigated a novel model called the BiHDM (Bi-Hemispheric Discrepancy Model) to capture the asymmetric disparities in the two hemispheres irrespective of the levels of brain activity during emotional expression. The research evaluated the proposed BiHDM model against other methods on three publicly available EEG emotion datasets. The outcomes proved the BiHDM model's superiority and efficacy. Notably, on one of the datasets (SEED-IV), the BiHDM approach performed 4% better than the previous cutting-edge technique (Emotion-Meter). The model called BiDANN, which also considered differences between the left and right hemispheres, came closest to the performance of BiHDM, but BiHDM still outperformed it. This novel model offers improved accuracy in distinguishing emotional states from EEG data and contributes to the advancement of emotion recognition technology.

Eanes Torres Pereira et al. 2021 [116] outperformed a research review with an emphasis on emotion recognition of three distinct EEG datasets: DEAP, MAHNOB, and STEED. These datasets were characterized by different durations of the stimuli or emotional triggers used during EEG recording. The study aimed to identify the key characteristics that make an EEG dataset suitable for emotion recognition. They highlighted the importance of two key characteristics for emotion classification datasets: having publicly available and globally evaluated stimuli, similar to the LIRIS-ACCEDE dataset, and ensuring that the stimulus duration is sufficiently long to genuinely influence the subjects' emotional states. The research emphasized the need for standardized and well-structured EEG datasets for emotion recognition, as these datasets should ideally represent diverse responses and feature stimuli that are long enough to evoke genuine emotional reactions.

Shuaiqi Liu, et al.2021 [117] developed an algorithm for subject-independent emotion recognition based on EEG data. They introduced a novel feature extraction method called Dynamic Differential Entropy (DDE). DDE captures the dynamic changes in EEG signals over time and represents the time-frequency features associated with emotional states. This allows the algorithm to track how emotional states evolve. The DDE features were then placed as input data into a CNN for classification. To improve the convergence speed of the learning process, they used ReLu, a commonly used activation function in neural networks. The algorithm was tested on the SEED. It achieved high accuracy and sensitivity, outperforming existing emotion classification methods. The model obtained an accuracy of 97.56% and a sensitivity of 98.67%, indicating its effectiveness in recognizing emotions from EEG data. The researchers highlighted the clinical value of their algorithm, particularly in the diagnosis of conditions like schizophrenia and depression.

Juan Cheng et al 2021 [118] investigated a unique approach for emotion identification using EEG data. This method is simpler and more efficient than traditional approaches as it lacks the need for feature extraction and is less susceptible to hyperparameter choices. Their classification model is not highly sensitive to hyperparameter settings. Selecting the appropriate collection of hyperparameters for deep learning or vintage algorithms for machine learning can be complex and time-consuming. They tested their method on two publicly available EEG databases commonly used in EEG-based emotion recognition: DEAP and DREAMER. The average accuracy of the results on the DEAP database was 97.53% for arousal and 97.69% for valence, respectively. The average accuracy for valence, arousal, and dominance on the DREAMER database was 89.03%, 90.41%, and 89.89%, respectively.

Zhen Liang et al.2021 [119] designed a model to capture both spatial and temporal dynamics in brain activity and does so through a combination of deep learning techniques, specifically deep convolutional recurrent generative adversarial networks (CNN-RNN-GAN). The primary goal of EEGFuseNet is to determine low-dimensional and deep features in high-dimensional EEG data. It focuses on capturing the dynamics in both the spatial distribution of brain activity and how these dynamics change over time. The researchers evaluated the effectiveness of EEGFuseNet's deep feature extraction in the context of unsupervised emotion recognition. They used three publicly available emotion databases for this evaluation. The researchers compared the performance of their unsupervised EEGFuseNet with other supervised methods. They found that the unsupervised method yielded comparable results in emotion recognition, demonstrating its effectiveness even without the use of labeled data. The accuracy rates and F1 scores for recognizing dominance, predictability, valence, and arousal were competitive.

Zhongke Gao et. al. 2021 [119] suggested the Channel-Fused Dense Convolutional Network (CDCN), a modern deep learning framework, for achieving the objective of EEG-based emotion identification. The researchers conducted extensive experiments on two well-known EEG emotion datasets, namely the SEED and DEAP datasets. On the SEED dataset and the DEAP dataset, the CDCN framework exhibited impressive average accuracies of 90.63% and 92.58%, respectively. These accuracies outperformed many other studies in the field. Moreover, the CDCN model remained consistently effective, surpassing 84% accuracy for within-subject tasks on the SEED dataset. The CDCN model was compared to six other methods, which achieved accuracy rates ranging from 67% to 89%. The CDCN model significantly outperformed these competing methods, particularly excelling on the DEAP dataset, where it achieved outstanding accuracy. The recommended framework is a viable method for emotion recognition tasks based on EEG data since it effectively extracts features from EEG signals taking into consideration electrode correlations and temporal dependencies.

Poomipat Boonyakitanont et al 2021 [120] Author focuses on improving the detection of epileptic seizure episodes in long EEG recordings and determining when these seizures start and end. This is an important task in epilepsy diagnosis and treatment. The researchers proposed a method called "ScoreNet" which involves two sequential steps. They tested their method using the CHB-MIT Scalp EEG database and contrasted it with other classifiers including logistic regression, CNN, and random forest. Comparing approaches that solely looked at individual EEG epochs, the results showed that Score Net greatly increased seizure detection performance. F1 scores went from 16–37% to 53–70%, and hourly false positive rates dropped from 0.53-5.24 to 0.05-0.61. This means the method had better accuracy in identifying seizures and reduced the number of false alarms. They aimed to provide clinically acceptable latency in detecting the onset and offset of seizures, which they referred to as the "effective latency index" (EL-index). This index helped measure the delay between when a seizure started or ended and when it was detected.

Tanvir Mahmud et al 2021 [121] present an innovative automated approach for detecting sleep apnoea frames in EEG signals. A person with sleep apnoea experiences frequent cessations and starts breathing while they are asleep. Traditional methods for detecting sleep apnoea often involve extracting features directly using the VMD algorithm which helps in separating the various modes of the EEG data from the signals. The decomposed EEG signals from the VMD are then processed by a deep learning model, specifically a fully convolutional neural network. This network operates in parallel on each VMD mode, extracting temporal features while maintaining their temporal dependencies. The results of their study show that their proposed method, which combines end-to-end deep learning with VMD, outperforms other approaches in all evaluation metrics. Specifically, it significantly improves sensitivity by more than 2%, which is a substantial improvement when it comes to disease diagnosis schemes, as it means the method is better at identifying sleep apnea events.

Feifei Qi et al 2021 [122] recommended an innovative strategy known as "spatiotemporal-filtering-based channel selection" or (STECS) which provided the objective of automatically determining the total number of informational EEG channels by taking advantage of both the spatial and temporal information present in EEG data. This involves jointly optimizing spatial and temporal filters, which collectively characterize the spatial and temporal patterns in the EEG data. The outcomes pointed out that the classification accuracies achieved by STECS were consistently higher than those obtained using another method called SSP-R, especially as the number of selected channels (k) increased. STECS is a method designed to automatically choose the most relevant EEG channels by leveraging the spatiotemporal characteristics of EEG data.

Tahrat Tazrin et al 2021 [123] introduced a novel framework called "Logic-in-Headbands based Edge Analytics" or LiHEA. The main objective of LiHEA is to seamlessly integrate EEG analysis with consumer-grade EEG headsets the researchers aim to make EEG analysis accessible and practical for everyday use by incorporating it into widely available consumer-grade EEG headsets. They adopted a special feature selection method for selecting the EEG signal features that are most important, particularly in cases of confusion. They also explored the performance of other models, such as KNN, SVM, and logistic regression on different datasets. These models achieved varying levels of accuracy, with the highest reaching 67% for KNN and 65% for logistic regression. They provided the LiHEA framework as a way to easily combine EEG analysis with EEG headbands that are easily accessible but have limited resources.

Anthony D. Bateson et al 2021 [124] the researchers aimed to create and evaluate a versatile EEG platform that seamlessly incorporates a Smartphone. The primary goal was to create a 19-channel EEG device that might be used to store data on a smartphone over a Wi-Fi network. They conducted a comparative analysis by pitting their Smartphone-based EEG system, known as "io: bio," against an FDA-approved clinical-grade EEG device. They designed and developed the io: bio Smartphone-based EEG system, which is intended for a wide range of applications. This finding suggests that the Smartphone-based system has the potential to be used in various applications and environments, making EEG data collection and analysis more accessible and adaptable for a wide range of research and clinical purposes.

Muhammad Yazid et. al. 2021 [125] a highly effective method for extracting features from EEG recordings to detect autism. Their method combines the Local Binary Pattern Mean Absolute Deviation (LBPMAD) and the recently suggested Local Binary Pattern Transition Histogram (LBPTH) with the DWT. Their method achieved remarkable classification accuracy. It achieved accuracy rates exceeding 99.6% for both SVM and KNN classifiers. Despite its high accuracy, the proposed method maintains a comparatively tiny feature vector size, with just 18 features. The method is versatile and capable of handling short input signals. Even with a reduced input signal length of only 512 data points (equivalent to 2.95 seconds), over 99.1% SVM classification accuracy was attained. Due to its high accuracy, small feature size, and low computational requirements, the proposed method is well-suited for integration into mobile, low-power, and cost-effective wearable medical devices.

Benedetta Olmi et al 2021 [126] present a summary of the technologies developed over the past ten years for neonatal seizure detection (NSD). The research indicates that EEG-based NSD systems tend to outperform those based on other electrophysiological signals. The study evaluates the performance of various expert systems, both EEG-based and ECG-based, using setups that are patient-specific and patient-independent. This evaluation helps determine the effectiveness and reliability of these systems as support tools for medical employees in NICUs. While EEG-based systems demonstrate superior performance, there is growing interest in exploring ECG as an additional marker for brain damage associated with neonatal seizures.

Tee Yi Wen et al. 2022 [127] investigate the occurrence of subjective bias in evaluating people's stress response when using clustering techniques and SVM classification to better understand and classify stress levels objectively. SVM was used to classify these pre-labeled stress levels, which was expected to lead to more accurate results compared to traditional subjective assessments. In this research, the researchers reported that while the KNN algorithm achieved an accuracy of 74.43% in classifying stress into three levels, SVM was not as effective for this task, achieving only 52.3% accuracy in a two-class classification. The most significant improvement came when the right prefrontal cortex's beta power data exhibited an astounding 98% accuracy, recommending that their hybrid strategy of combining SVM and k-means clustering was successful in minimizing individual variations in stress reactions, ultimately leading to more reliable and accurate mental stress detection.

Ruiqi Fu et al.2022 [128] researchers adopted a novel deep neural network called the (SDCAN) Symmetric Deep Convolutional Adversarial Network for classifying stress levels based on EEG data. This innovative network combines CNN architecture with adversarial theory. The primary goal of this research was to manually distinguish discriminative and invariant characteristics from unprocessed EEG data using the adversarial inference technique which intends to boost the network's capacity and the precision of stress level classification to generalize its findings across different individuals. The results of their study demonstrated that the SDCAN network outperformed conventional CNN methods in classifying stress levels has achieved higher accuracies of 87.62% and 81.45% for classifying four and five different stress stages which indicates that the SDCAN network was more effective in distinguishing between various levels of stress based on EEG data when compared to traditional CNN approaches.

Amir H. Ansari et al. 2022 [129] identified a novel variation of the Inception block within CNN called "Sinc." This innovative Sinc block was designed to classify sleep stages in preterm infants utilizing EEG information. The principal characteristic of the stated Sinc block can perform multi-scale analysis, which allows it to focus on sequential EEG information while being a reduced amount dependent on the number of EEG channels available for analysis. The results of their study demonstrated that the Sinc-based model outperformed existing state-of-the-art algorithms designed for detecting neonatal quiet sleep and achieved a mean Kappa value of 0.77 ± 0.01 when using 8-channel EEG data and 0.75 ± 0.01 when using a single bipolar channel EEG which indicates that the Sinc network was highly effective in accurately classifying sleep stages in premature newborns. The study employed statistical analyses, including 95% confidence intervals and bootstrap hypothesis testing, which further confirmed the statistical superiority of the Sinc model.

Hanwen Wang et al. 2022 [129] propose presented a novel approach for concealed information detection using EEG data. Their framework aimed to elicit specific brain responses associated with concealed information ensuring that the subject remained attentive and focused using a technique called Rapid Serial Visual Presentation (RSVP) for detecting deception. The proposed framework, called RCIT (which stands for Rapid Serial Visual Presentation and Concealed Information Test), effectively induced distinctive brain wave patterns for deception detection and was resistant to countermeasures providing an accuracy rate of 87.13% in detecting concealed information that used RSVP and an autoencoder achieving promising results in detecting deceptive responses while maintaining subject focus.

Parthana Sarma et al.2022 [130] proposed a technique for identifying emotions using EEG data. This method is designed to identify segments of EEG data associated with strong emotional responses, and it selects relevant EEG channels automatically for this purpose. The results indicated that the higher frequency EEG sub-bands (beta and gamma) with 15 channels showed the highest classification accuracy, peaking up to 95%. These segments related to emotions were found to occur at specific times during the EEG recording: from the start to 75% of the experiment duration for both favorable and indifferent feelings, and from 25% to 75% for negative emotions. The proposed method was also rigorously tested and validated, including assessing PLV values in channel selection, conducting (LOTO) Leave-One-Test-Out and LOSO

(Leave-One-Subject-Out) experiments, subjective analysis, and considering various parameters for the k-NN algorithm. The results show a high level of accuracy in recognizing emotions, especially for higher-frequency EEG subbands.

Guofa Li et al 2022 [131] investigated a motion recognition based on EEG data that offers several advantages. They conducted experiments using various classifiers to assess the effectiveness of their method. They selected specific features from EEG data and applied batch normalization (BN) to normalize these features. These classifiers employ algorithms to categorize EEG data according to various emotional states. One notable finding in their research was that using a small subset of the available electrode channels (fewer sensors) for emotion recognition can yield nearly identical or even better accuracy compared to using all available channels. This suggests that high accuracy can be achieved with a simplified EEG setup, which has practical implications for real-time emotion recognition systems. The application of batch normalization at the experiment level further improved recognition accuracy over which there is an increase from 73.33% to 89.63% through LR classifier.

Alireza Samavat et al 2022 [132] proposed a distinctive approach for using raw EEG waves to identify emotions. Their approach is a deep learning model that combines both CNNs and Bi-LSTM. They introduced a deep learning model that handles several raw EEG data inputs. These EEG shows brain activity, which is normally obtained from 62 electrode channels. The combination of CNNs and Bi-LSTM allows their model to capture both temporal patterns and frequency components in the EEG signals. Their approach is a deep learning model that takes raw EEG signals as input and uses a combination of CNNs and Bi-LSTM to extract important features for emotion recognition. The adaptive regularization technique enhances the model's performance by considering the spatial aspects of the EEG channel electrode.

Kin Ming Puk et al 2022 [133] Researchers presented an efficient pattern recognition framework for identifying discrete emotional states, specifically happy, angry, and neutral emotions, using EEG signals. Emotions are complex, and they wanted to create an automated system that could accurately categorize these emotions based on brainwave data. EEG data provides a wealth of information, and many features can be extracted to capture different aspects of brain activity associated with emotions. They aimed to create a quantitative framework to characterize different emotional states based on EEG data. The proposed methodology in their study yielded the best performance compared to three other baseline models. They compared different models and found that Sparse Group Lasso (SGL) and SVM performed well in organizing emotions, with the sparse model (SGL) being particularly efficient in selecting relevant features.

Yong Peng et al 2022 [134] introduced a novel approach called EEG-based emotion recognition which provides optimal graph-coupled semi-supervised learning (OGSSL). Their model integrates emotion identification and adaptive graph learning into a single, cohesive goal. They conducted experiments using the SEED-IV dataset to assess the performance of this approach and to analyze the relationship between brain regions and emotions. The OGSSL model demonstrated excellent average accuracy in a trio of obstacles for recognizing emotions across sessions, achieving an accuracy of 76.51%, 77.08%, and 81.29%. The results of the investigation concluded that the presence of emotions was more closely associated with the gamma frequency band as well as certain brain regions, including the left and right temporal, prefrontal, and (central) parietal lobes. OGSSL consistently outperformed the other models, with average accuracies ranging from 76.51% to 81.29%.

Yong Peng et al 2022 [135] researchers proposed a model called S3LRR generally known as Semi-Supervised Sparse Low-Rank Regression for EEG-based emotion recognition which aims to integrate two critical aspects of the emotion recognition process of discriminative subspace identification and semi-supervised learning. This research evaluated the performance of S3LRR in recognizing specific emotional states which achieved the highest recognition accuracy of 83.96% for the "fear" condition and the lowest precision of 63.95% for the "sad" state. With comparatively low rates of misclassification for other emotional states, 83.96% of EEG samples were classified as being in the "fear" state. In cross-session emotion recognition tests, the benefits of S3LRR were very noticeable. Compared to the outcomes of another model (RLSR), S3LRR showed significant improvements in accuracy, with increases of 6.94%, 5.83%, and 5.22% for the three recognition tasks.

Jia Wen Li et al 2022 [136] developed a technique called Brain Rhythm Sequencing (BRS) for interpreting EEG data based on the dominant brain rhythm at specific time intervals in interest to create a time-series sequence of EEG data, where each timestamp is associated with the most dominant brain rhythm occurring at that moment. The research they carried out, used three emotive datasets (SEED, DEAP, and MAHNOB) to examine music emotion recognition (MER), and showed classification accuracy ranging from 70% to 82%. When comparing their approach to existing state-of-the-art methods with the same number of channels, they found that their approach performed slightly better, with accuracies surpassing 70% for various test sets. However, the suggested strategy, which used a single channel with a 10-second duration, outperformed approaches that aggregated multiple less significant channels by a small margin.

Sun-Hee Kim et al 2022 [137] proposed a novel combination approach for analyzing emotional states, referred to as WeDea analysis. The dataset they compiled, named WeDea, is intended for use in emotion recognition studies. To validate the effectiveness of their new EEG dataset, the researchers developed an emotion recognition framework. When compared to the multi-SVM classifier, the LSTM classifier produced results that were 4% better. WeDea demonstrated substantially higher classification accuracy utilizing the multi-SVM classifier when compared to three other well-known datasets (DREAMER, DEAP, and SEED), with improvements of 10.7%, 15.7%, and 9.7%, respectively. Similarly, with the LSTM classifier, WeDea demonstrated improvements in classification accuracy of 10.4%, 14.3%, and 10.2% when compared to these datasets. One of the most distinctive features of EEG data is its capacity to track real-time human brain activity at a millisecond temporal resolution.

Guangyi Zhang et al 2022 [138] investigated a novel approach called "PARSE" for performing emotion recognition using EEG data. The primary goal of their research is to create a model that can effectively recognize emotions based on EEG signals, even when there is a limited amount of labeled data available. The results showed that PARSE consistently outperformed other methods, especially when there were very few labeled samples available (1, 3, 5, 7, 10, or 25 per class). The model's performance benefited from representation alignment, particularly when dealing with imbalanced class distributions. The proposed research for EEG-based emotion recognition excels at learning from limited labeled data. It combines several techniques, including label guessing, data augmentation, and representation alignment, to achieve impressive results in emotion classification tasks, outperforming other state-of-the-art methods.

Busra T. Susam et al 2022 [139] The researchers emphasize adopting machine learning tools to differentiate between various resting states in young people with autism spectrum disorder (ASD) both before and after engaging in a quick mindfulness meditation activity known as "MF" (Mindfulness Meditation). The classifier achieved an average accuracy of 80.76%, sensitivity (correctly identifying Pre-MF) of 78.24%, and specificity (correctly identifying Post-MF) of 82.14%. These results show that machine learning is effective in distinguishing between different neural states in individuals with ASD. This indicates that specific patterns of brain activity in certain regions were informative in characterizing the resting states. The research verified that the distinction between the Pre-MF and Post-MF states was prompted by the MF meditation practice, as opposed to a linear-temporal drift.

MD. Shafayet Hossain et al.2022 [140] proposed three innovative techniques for the correction of motion artifacts in single-channel EEG and fNIRS (functional Near-Infrared Spectroscopy) signals. These techniques were designed to enhance the quality of these physiological signals by reducing the interference caused by motion artifacts. VMD was employed as the primary technique for motion artifact correction. VMD is paired with Canonical Correlation Analysis (CCA) to further enhance its capability to reduce motion artifacts in these physiological signals. SNR and percentage reduction of motion artifacts were the metrics used by the researchers to assess the efficacy of these three innovative strategies. VMD-CCA demonstrated the best denoising performance for EEG data out of the three approaches when it was broken down into 15 IMFs. For all 23 EEG recordings, it produced an average SNR improvement of 23.81 dB and a 57.01% decrease in motion artifacts. Also, they found that all three VMD-based approaches provided significant artifact reduction, with average percentage reductions ranging from approximately 53.59% to 55.86% for all trials.

Hanqi Wang et al 2023 [141] introduce an innovative approach based on EEG emotion recognition and explain how they've tested their idea using three well-known EEG-dependent models on the DEAP dataset. Researchers lent a method for limiting or defining the precise areas of interest in EEG data. This method uses context information when perturbing the input data, which is a way of introducing small changes or disturbances to the data to better understand how the model responds. To evaluate the effectiveness of their context-aware perturbation method, they adopted the Arousal dimension from the DEAP dataset to perform ablation research and a specific EEG-based model called "TSception." This study likely involves analyzing how the model performs when the context information is included or omitted from the perturbation process.

Chunguang Chu, et al 2023 [142] Introduced an enhanced framework for the recognition of EEG microstates using deep neural networks. This framework achieves recognition rates ranging from 90% to 99%, making it highly accurate. Additionally, it effectively handles artifacts that often interfere with EEG data analysis. In interest to determine the activated functional brain areas connected to each microstate class, the study also makes use of a visualization method known as gradient-weighted class activation mapping. The primary goal of their research is to enhance the recognition of EEG microstates using deep learning. Microstates are brief and distinct patterns of neural activity that provide insights into the functioning of the brain. They employ deep learning techniques to achieve optimal microstate identification and to map the activated brain regions corresponding to different microstates. The study explores the characteristics of EEG microstates and their clinical relevance.

Kunyuan Zhao et al 2023 [143] propose an innovative approach to emotion classification using EEG data and food images as visual stimuli. What sets this research apart is its focus on using a portable single-electrode EEG device for emotion recognition, which is a significant breakthrough. The researchers used food images as visual stimuli to elicit emotional responses from participants. Simultaneously, they collected EEG data using a single-electrode EEG device. This technique efficiently retrieves single-channel EEG characteristics with Extreme gradient boosting (XGBoost) which was the classifier of choice for their emotion categorization system. The researchers achieved an optimal accuracy of 94.76% in their single-channel EEG classification model. This result was remarkable because it matched the performance of traditional multi-channel EEG classification models.

Dong Wen et al 2023 [144] proposes a feature extraction method for EEG signals to improve cognitive training analysis. The key component of their approach is a feature extraction method called "permutation conditional mutual information common space pattern" (PCMICSP). PCMICSP is used to extract informative features from EEG signals. It's based on the concept of mutual information, which quantifies the statistical dependence between two variables. The primary novelty of PCMICSP is the mutual information matrix, which takes place alongside the covariance matrix utilized in the original CSP method. The linear and nonlinear relationships found in EEG signals are taken into consideration in this matrix. This change allows CSP to construct spatial filters based on both types of correlations.

Xingyi Wang et al 2023 [145] researchers aimed to enhance the efficiency of resources in EEG-based emotion classification by employing self-supervised learning methods. To recognize emotions along with finishing the pretext task, they adopted a deep multi-task CNN. Both the SEED dataset and the DEAP affective dataset, which are widely used for EEG-based emotion classification tasks, are publicly available datasets on which they conducted significant experiments. For instance, with a 40% data volume, they achieved approximately 99% accuracy in valence and arousal classification. Their results demonstrated that self-supervised learning had a stabilizing effect on classification metrics. This methodology is an important addition to the field of emotion categorization using EEG signals since it demonstrates itself to be both efficient and successful, particularly when working with minimal data.

Andreas Miltiadous et al. 2023 [146] the researcher provided a comprehensive evaluation of the signal processing and classification methodologies used in the context of different EEG databases. Their objective is to provide significant perspectives for upcoming investigations in the domain of EEG-based signal processing and categorization. They meticulously evaluate the methodologies applied to various EEG databases. Notably, there's a strong connection between the Bonn and CHB-MIT databases, with almost half of the studies involving multiple databases utilizing this combination. Additionally, the combination of the Bonn database with the Neurology Sleep Center database is also significant, accounting for a substantial portion of multiple database studies.

Table 2.1 Summary of literature review for various EEG techniques.

Detail of the journal/ Book / Book chapter/ website link	**Year of Publication**	**Main findings or conclusion relevant to the proposed research work**
Sensors 16, no. 10 (2016): 1558.	2016	Combining wavelet and scalogram transformations, neurophysiological inputs are processed to identify emotions and arranged into frames resembling a grid.
IEEE international conference on bioinformatics and biomedicine (BIBM) (pp. 352-359). IEEE.	2016	The F-score metric method revealed that evaluating channels are a unified entity resulting in better performance in reducing the number of channels while maintaining acceptable accuracy levels.
Applied Sciences 7, no. 12 (2017): 1239.	2017	Significant increase in the number of publications related to EEG-based emotion detection which suggests a

		growing interest among researchers in utilizing EEG technology for emotion recognition
Sensors 17, no. 5 (2017): 1014.	2017	Adaptive subspace feature matching (ASFM) to address the challenge of integrating marginal and conditional distributions in emotion recognition from EEG data which plans to align the allocation of data in EEG from a base domain with those of a target domain
Technology and health care 26, no. S1 (2018): 509-519.	2018	The accuracy of emotion recognition from EEG signals is influenced by different frequency bands and varying numbers of EEG channels.
Procedia computer science 132 (2018): 752-758.	2018	Feelings are essential to our day-to-day existence which sought to analyze their effects using EEG technology emotions could indeed be recognized from EEG signals, with an average accuracy of 60%.
IEEE Access, 7, pp.44317-44328.	2019	Increase the precision of emotion identification with EEG data by employing an end-to-end automatic learning approach that can automatically extract emotional features from EEG signals in both spatial and temporal dimensions.
IEEE Transactions on Affective Computing 12, no. 4 (2019): 832-842.	2019	Participants' feelings were depicted in the video clips, both positive and negative, and simultaneously collecting and processing EEG data. And also received instant feedback after each clip.
IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 50, no. 11, pp. 4408-4414, Nov. 2020, doi: 10.1109/TSMC.2018.2850323.)	2020	Focused on stop signal task (SST), to learn more about the neural mechanisms underlying the inhibition and go tasks, called Event-Related Spectral Perturbation (ERSP) to study EEG.
IEEE journal of biomedical and health informatics. PP. 10.1109/JBHI.2020.3025865.)	2020	Proposed limited source data where the subject-transfer method is more effective than other methods in selecting informative training data for efficient transfer learning in EEG decoding
IEEE Transactions on	2020	Focused on individuals with Intellectual

Neural Systems and Rehabilitation Engineering, vol. 28, no. 11, pp. 2420-2430, Nov. 2020, doi: 10.1109/TNSRE.2020.3024937.)		and Developmental Disorders (IDD) to uncover specific characteristics of the IDD group's brain networks to scrutinize the effects of soothing music on the networks
IEEE Access, vol. 8, pp. 46131-46140, 2020, doi: 10.1109/ACCESS.2020.2978391)	2020	Introduced a multi-biosignal wearable wireless interface for sleep analysis that enables convenient sleep tracking using Polysomnography (PSG)
IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 2, pp. 453-464, Feb. 2021, doi: 10.1109/JBHI.2020.2995767.)	2020	EEG-based emotion recognition differentiates itself from conventional methods as it doesn't necessitate feature extraction and is less sensitive to the hyperparameter.
IEEE/ACM Transactions on Computational Biology and Bioinformatics, vol. 18, no. 5, pp. 1710-1721, 1 Sept.-Oct. 2021, doi: 10.1109/TCBB.2020.3018137.)	2020	Brainwave signals based on EEG data are addressed to challenge identifying emotions in individuals.
IEEE Access. PP. 1-1. 10.1109/ACCESS.2020.3044732.)	2020	WLnet was conducted using four different methods: CSP, TCSGSP, EEGNet, and WLnet itself in both stressful and not stressful milieu for training and testing the models.
IEEE Access, vol. 9, pp. 117338-117348, 2021, doi: 10.1109/ACCESS.2021.3099492.)	2021	Developed learning algorithms for SNNs and demonstrate the potential applications of SNNs in processing spatiotemporal data, particularly EEG data
IEEE Transactions on Affective Computing, vol. 12, no. 2, pp. 494-504, 1 April-June 2021, doi: 10.1109/TAFFC.2018.2885474	2021	Two neural network models, BiDANN and the improved BiDANN-S specifically designed to make emotion recognition from EEG data less which helps the model work well across different people
IEEE Transactions on Affective Computing, vol. 12, no. 1, pp. 203-214, 1 Jan.-March 2021, doi: 10.1109/TAFFC.2018.2866865.)	2021	Demonstrated the potential of using advanced sensors like the Empatica E4 uses physiological information to anticipate human emotional states in real-time.

IEEE Transactions on Affective Computing, vol. 12, no. 1, pp. 154-164, 1 Jan.-March 2021, doi: 10.1109/TAFFC.2018.2854168.)	2021	Evaluated three different EEG datasets, namely DEAP, MAHNOB, and STEED, which focused on emotion recognition during EEG recording.
IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 7, pp. 2533-2544, July 2021, doi: 10.1109/JBHI.2021.3049119.)	2021	Embraced the FLDNet, a cutting-edge deep learning system intended to capture significant connections from different frames.
IEEE Transactions on Cognitive and Developmental Systems, vol. 13, no. 2, pp. 354-367, June 2021, doi: 10.1109/TCDS.2020.2999337.)	2021	BiHDM aims to capture the asymmetric variations in the two hemispheres' brain activity during emotional expressiveness.
IEEE Sensors Journal, vol. 21, no. 13, pp. 14923-14930, 1 July1, 2021, doi: 10.1109/JSEN.2021.3070373.)	2021	a hybrid method that combined CWT-based EEG signal processing with forefront CNN models for extracting deep features
IEEE Journal of Translational Engineering in Health and Medicine 9 (2021): 1-7.)	2021	Focused on the connection between EEG and HRV under stress conditions
IEEE Access, vol. 9, pp. 72535-72546, 2021, doi: 10.1109/ACCESS.2021.3078470.)	2021	Design an Integrated Safety Management System (ISMS) that incorporates CNN and LSTM.
IEEE Transactions on Consumer Electronics, vol. 67, no. 2, pp. 166-175, May 2021, doi: 10.1109/TCE.2021.3079399.)	2021	Kriging methods were applied for efficient seizure detection devices, created especially for an environment of edge computing by viewing the brain as a spatial panorama.
IEEE Transactions on Cognitive and Developmental Systems, vol. 14, no. 2, pp. 541-551, June 2022, doi 10.1109/TCDS.2021.30534	2021	Framework ensured that the subject remained attentive and focused using a technique called Rapid Serial Visual Presentation (RSVP) to detect deception.

55.)		
IEEE Transactions on Neural Systems and Rehabilitation Engineering. PP. 1-1. 10.1109/TNSRE.2021.3111689.)	2021	Designed a model to capture both spatial and secular dynamics in brain activity through a combination of deep convolutional recurrent generative adversarial networks (CNN-RNN-GAN).
IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 29, pp. 2474-2483, 2021, doi: 10.1109/TNSRE.2021.3129467)	2021	Improved the detection of epileptic seizures when to start and end which proves to be an important task in epilepsy diagnosis and treatment
IEEE Trans Neural Syst Rehabil Eng. 2022;30:1384-1400. doi: 10.1109/TNSRE.2022.3174821. Epub 2022 May 30. PMID: 35584065.)	2022	The adversarial inference technique augments the accuracy of stress level classification and improves the network's ability to generalize its findings across different individuals.
IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-12, 2022, Art no. 4000812, doi: 10.1109/TIM.2022.3147876.)	2022	LOTO and LOSO performed subjective analysis, which helps to calculate the effectiveness and competence of the draw near emotion recognition using EEG data
IEEE J Biomed Health Inform. 2022 Mar;26(3):1023-1033. doi: 10.1109/JBHI.2021.3101117. Epub 2022 Mar 7. PMID: 34329177.)	2022	A novel variation within CNN called "Sinc." was designed to classify sleep stages in untimely newborn babies using EEG data.
IEEE Sensors Journal, vol. 22, no. 11, pp. 10751-10763, 1 June 1, 2022, doi: 10.1109/JSEN.2022.3168572.)	2022	Batch normalization (BN) technique was used to normalize and helped improve the consistency and comparability of the features across different individuals.
IEEE Access, vol. 10, pp. 24520-24527, 2022, doi: 10.1109/ACCESS.2022.3155647.)	2022	Developed a technique that combines CNNs and Bi-LSTM which improves the accuracy of emotion recognition.

Table 2.1 represents the analysis of various techniques which are available for EEG. The fact that the methodologies being evaluated differ widely in terms of the characteristics gathered, the classification algorithm that is utilized, and the applicability of the system makes it far more difficult to choose algorithms for real-time deployments. To assist in dispelling this uncertainty, the next section will categorize various methods according to their degree of accuracy, application domain, characteristics made use of, and level of computational complexity. Academics and system designers may find it easier to identify which algorithmic implementation is most appropriate for a certain job as a result of this.

2.2 STATISTICAL EVALUATION OF THE COMPARED TECHNIQUES

Accuracy and the amount of computational complexity are examined as part of the performance evaluation of the suggested models, which is based on the characteristics and application types that are used. Comparing EEG signals in both real-time and dataset modes indicates that they are comparable to one another. This comparison also demonstrates that CNN models and their modifications perform finer than the other models in terms of absolute levels of categorization accuracy.

Figs 2.1 and 2.2 show this point by comparing the two techniques' accuracy in the context of EEG application. This makes it easier to pick acceptable algorithms for future research by highlighting the similarities and differences between the two approaches. In dataset-based classification, it has been found that FLDA, ANN, PNN, and LS-SVM all perform well; however, 2D CNNs employing KELM, kNN, and RF methods have shown to be more successful in real-time EEG classifications [147] [148] [149] [150] [151]. The following figure, which depicts algorithms and their degree of computational complexity, shows a comparison that is comparable concerning the level of computational complexity possessed by each of the systems.

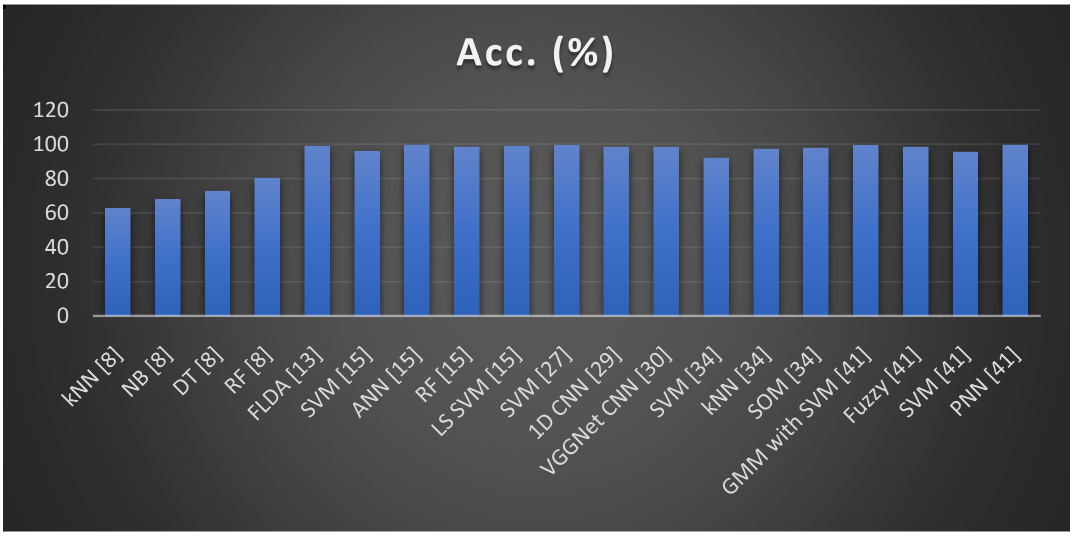

Figure 2.1 Accuracy comparisons for dataset-based algorithms

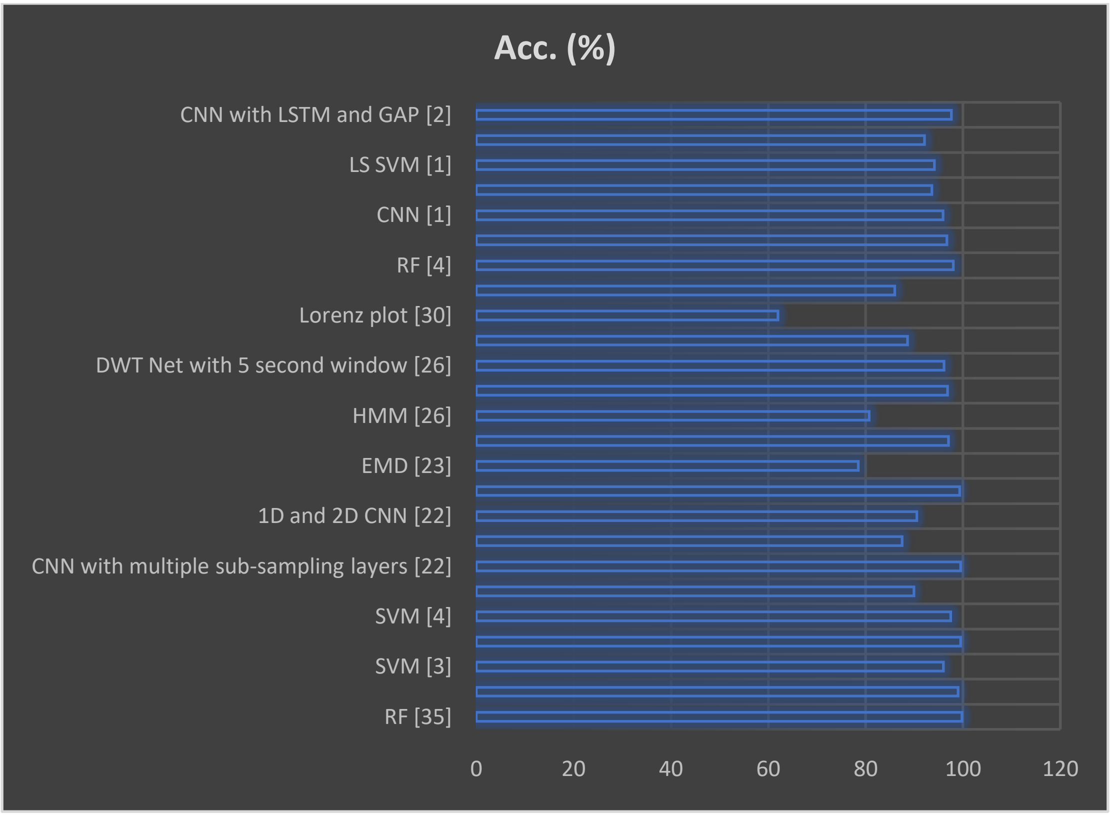

Figure 2.2 Accuracy comparisons for real-time algorithms

Along with other kinds of neural network models, CNNs, RNNs, and PNNs have an exceptionally high computational cost. This is due to the many feature extraction layers included inside these models. The figure elucidates this point for the reader clearly and convincingly. As can be seen in Figure 2.3, the majority of models belong to the category of having a degree of complexity that is somewhere in the middle, but kNN, SVM, and numerous other non-neural models have a level of complexity that is much lower [152] [153] [154] [155] [156]. The results demonstrate that, in terms of accuracy and computational complexity, the SVM, FLDA, and CNN models are the most appropriate choices for EEG classification.

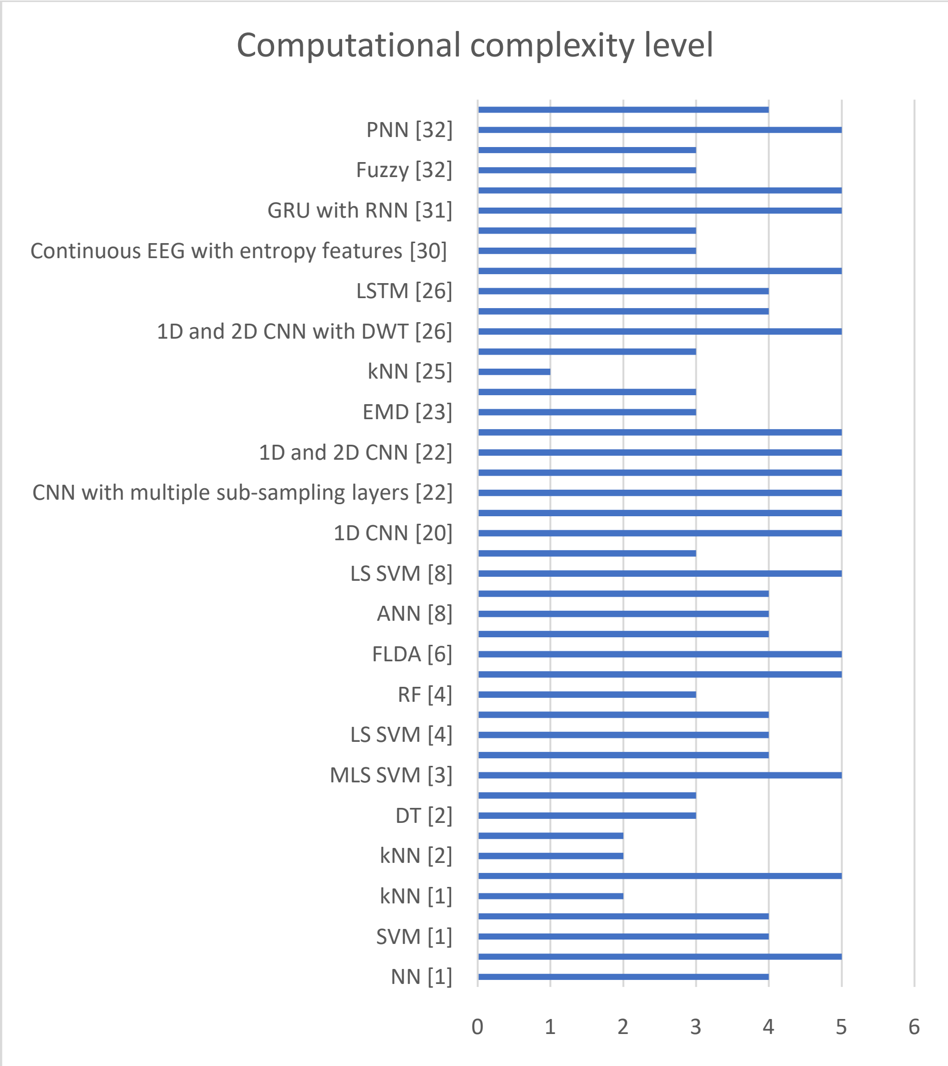

Figure 2.3 Computational complexity levels of different algorithms

2.3 CONCLUSIONS

According to the findings, the CNN, SVM, and FLDA algorithms are superior to those of their competitors both in terms of accuracy and the level of complexity required to apply them. When it comes to modeling dynamic and static data in real-time, these approaches provide the system a significant advantage thanks to the advantages they bring. The use of these approaches has the potential to increase both the classification accuracy and the practicability of the existing transfer learning models. Combining these models with ECG and other body metrics allows for a high level of accuracy to be achieved in the data categorization process. It is probable that in the not-too-distant future, it may be feasible to improve these models by merging transfer learning with basic classifiers, which would result in an ensemble of these techniques that is more successful for real-time scenarios.

CHAPTER 3

DESIGN OF A MULTISPECTRAL DATA REPRESENTATION ENGINE FOR CLASSIFICATION OF EEG SIGNALS VIA ENSEMBLE MODELS

"An opinion should be the result of thought, not a substitute for it."

- Jef Mallett

It is necessary to create multi-domain modules in interest to classify EEG signals. These modules need to conduct post-processing activities and comprise signal pre-processing and filtering, signal segmentation, feature extraction from segmented signals, statistical modeling for feature reduction, signal classification into one of N brain illness classifications, and feature extraction. For researchers to achieve these objectives, they have built a wide range of deep learning models. The bulk of these models explain EEG data using single-domain features. When applied for a wide variety of illnesses, this reduces the performance options available. In addition, when deep learning models are utilized, the procedures of feature extraction and selection are encapsulated inside black-box containers, which means that these containers cannot be altered in any way without harming the classification performance. In an interest to circumvent these limits, the research presented here recommends developing an engine for the representation of multispectral data that can identify EEG signals using ensemble models. Input EEG signals are converted by the recommended engine into iVector and MFCC. While the iVector is formed with the help of statistical entropy characteristics, the MFCC feature vector is built with the assistance of cepstrum, spectrum, power density, and other frequency domain datasets & samples. By improving the effectiveness of feature representation, the amalgamation of various feature sets may perk up classification performance for input EEG datasets & samples [157] [158] [159] [160]. Assessing the effectiveness of an existing ensemble classification model, a custom model is developed by leveraging MNNs with varying sizes of their layering structures.

Because of this fluctuation, the suggested model can recognize EEG signals according to a wide range of conditions, including Alzheimer's disease, stroke, brain tumors, sleep disturbances, and many more. The proposed model was used to classify a wide range of EEG ailments, including epilepsy, dementia, Alzheimer's type disease, and Parkinson's type disease, amongst others. It was shown that the proposed model has an accuracy level of more than 98.5% in categorizing various illnesses. When the act of the model was also matched up with many modern looms, under a range of input situations, it was discovered that the suggested model surpassed the current models because of accuracy, precision, recall, and delay performance [161] [162] [163]. As a consequence of these advantages, the technique that was described is useful for real-time clinical applications. The work's general progression is revealed in Fig. 3.1.

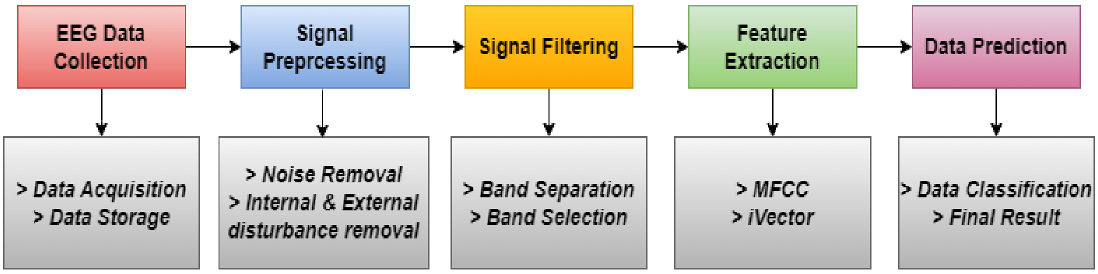

Figure 3.1 Implementation flow of proposed work.

3. 1 INTRODUCTION TO THE MULTISPECTRAL DATA REPRESENTATION MODEL

In interest to develop EEG classification models effectively, it is important to construct filtering out the signal, pulling out the region of interest (RoI), feature depiction, feature assortment, stratification, and activities involved in post-processing. For an EEG classification model to be considered highly successful, it must have both a low processing latency and a high efficacy of classification. Figure 3.2 is an illustration of a popular EEG classification model, which demonstrates how EEG data is interpreted into a variety of feelings. This approach reduces the effect of noise and other types of internal and external disturbances by using EEG data that has been pre-processed and obtained from real-time headsets. Among the temporal features that are retrieved from the data after filtering, those based on angular, spatial, and frequency-based feature vectors are some of the most common [164] [165] [166] [167]. People may be placed into one of many categories of brain illnesses or brain states based on these features, which serve as time-domain interpretations of the present state of the brain and can be used to classify patients.

In the model shown in Fig. 3.2, the SVM model is used in interest to categorize the collected data into a variety of different types of emotions. External systems can make use of these sensations in interest to identify user behavior and assist with psychometric analysis. It should come as no surprise that the processes of feature withdrawal, feature assortment, and categorizing blocks are major contributors to the overall performance of these models. The next part of this essay covers not only the layout of these blocks but also the performance attributes that came from a wide range of high-tech classification models as well [168] [169] [170]. Because of this conversation, it seems that these solutions either employ a black-box paradigm or are very general, together of which restricts how far they can scale in terms of how well they function in terms of latency and accuracy.

The following issues for real-time EEG datasets are also brought to light by the models that are now available:

These models' usage of uni-domain or bi-domain features, which in turn leads to a reduction in their real-time classification performance, have resulted in restricted feature representation capabilities for the models. Because deep learning models employ black-box methodologies, it is not possible to adjust or change their performance using linear optimization techniques. The model's applicability and scalability are both severely limited as a result of the dependence of classification accuracy on the density of the datasets & samples.

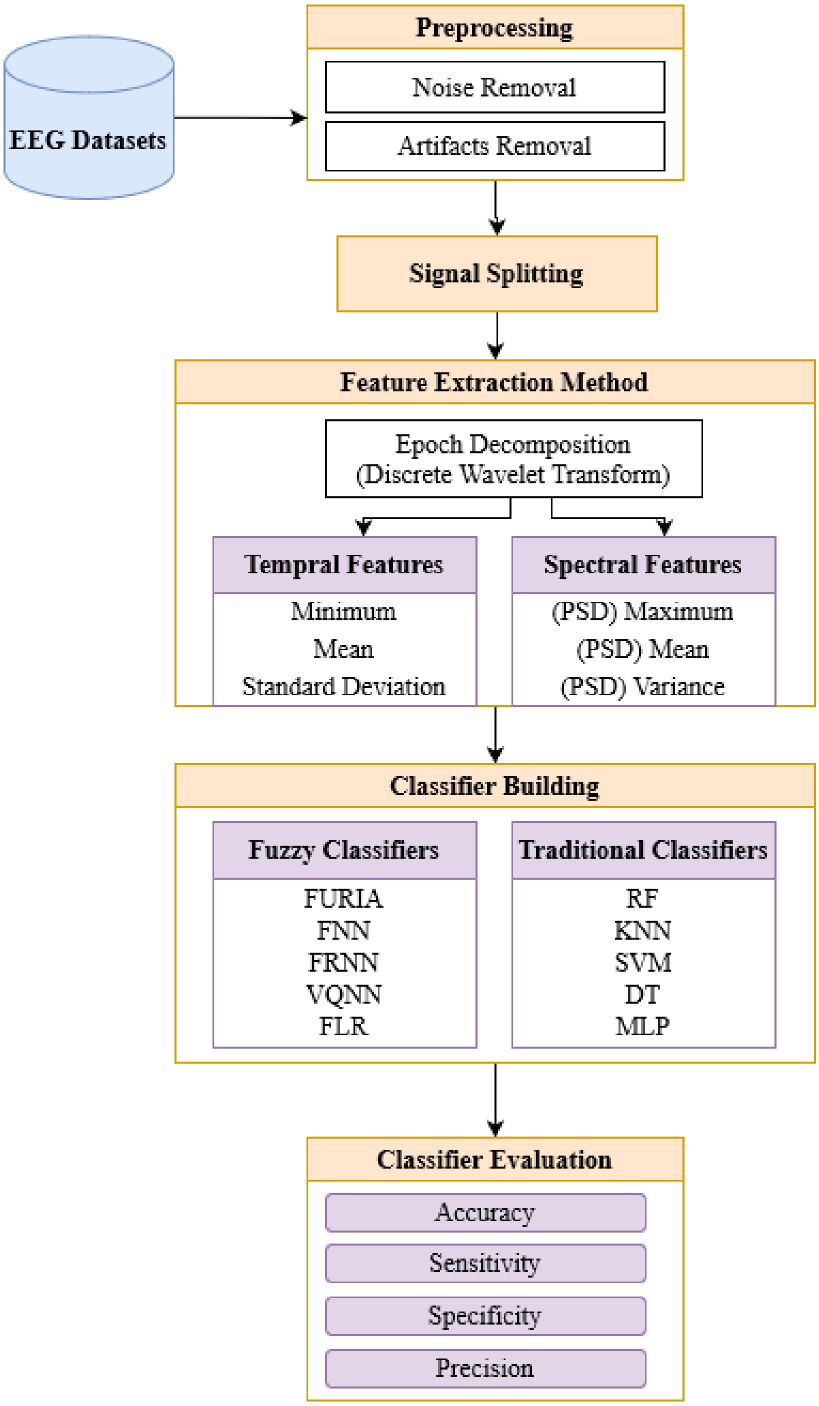

Figure 3.2 A general-purpose EEG classification model

The next part will look into the structural design of the superior feature assortment engine that is used for multivariate EEG categorization. It leads to get around issues with feature representation, sluggish performance, and limited precision. In the fourth part of this article, the outstanding accomplishment of this model is examined and matched up to a multiplicity of other approaches that are well thought-out to be high-tech methodologies. In conclusion, this study presents some insightful remarks on the proposed model as well as some ideas on ways to further improve the model's outstanding accomplishment for various circumstances.

3.2 EXISTING MODELS THAT PERFORM MULTISPECTRAL DATA REPRESENTATION ANALYSIS

In the course of research, numerous models have been constructed for a considerable length of time to characterize EEGs. What separates these models from one another is the applications they are most suited for, the degrees of precision and review provided, and the duration of time required to complete the task. For instance, the research that is presented in [101] [113] [114] investigates the use of an amalgamation of direct discriminant analysis (LDA), KNN, SVM, and ANN with normal spatial example (CSP) and Transfer TSK Fuzzy Classifier (TTFC) in interest to achieve improved characterization results. This investigation was carried out in interest to improve the accuracy of the characterization of the subject. Because these models include application-specific characterization qualities, the process of putting them into practice has to adhere to stringent accuracy standards in the interest of providing reliable results. Additional extensions to this model are investigated in [102] [103] concerning multidomain EEG groups. The Neuroglial Network Model (NNM) and low-force cantered ultrasound excitation (LIFUS) are cast off in these expansions. Because of the enormous computational complexity they have, these models are incapable of being scaled up for any substantial amount of time, despite the high degree of accuracy they have. This is the case although they have. The Multiple Recurrent Multilayer Neural Network (MFMBN) technique was reported in the study. MFMBN is an approach that, in contrast to previous models that have been published, allows one to attain more accuracy and enhanced flexibility. As a consequence of this project, the adaptability of the organization to changing conditions is going to be strengthened. Using CNN in conjunction with cross wavelet change (XWT), Local Binary Pattern Transition Histogram (LBP TH), and Multivariable Scale Mixture Model (MSMM), Scholars have constructed theoretically comparable models. These models, which use extended element extraction strategies, are utilized in the process of diagnosing epilepsy [171] [172] [173]. As a result, execution is both improved and thoroughly described.

As a direct consequence of the development of these element extraction models, a Hand-Crafted Deep Learning EEG model (HC DL), a quadratic classifier with wavelet highlights, and an MNN with Dilated Convolutions (MSNN DC) combination are now under consideration. Large-scale inclusion extractions are employed by these algorithms to handle EEG waveforms falling within a broad range and to obtain a more precise classification. In the interest of getting a more precise categorization, this step is taken. These models, on the other hand, only have a moderate degree of accuracy, which the study presented in [133] [134] [135] suggests has the potential to be enhanced. The study that is being discussed here examines a discriminatory progressive scanty depiction classifier, a temporal area successive components directly using an LSTM neural association and a DCNN neural structure. The precision of these models may increase as a direct consequence of our work. These models provide a contribution to the improvement of EEG highlights, which, in turn, facilitates order exactness manufacture for a wide range of remedial applications by making the process simpler to carry out. Comparable models are investigated in [120] [138] and the researchers who were responsible for writing those studies recommend using the Extended KNN and cooperative methods for dividing sources for the blind as a means of achieving more flexibility in terms of implementation. These are some of the strategies that may be of assistance to those who have vision impairment. These models make use of fairly basic approaches for highlight extraction; nevertheless, they are impossible to use in EEG datasets that have a comprehensive scope because of the simplicity of these methods [174] [175] [176] [177] [178] [179]. Because of this, it is simple to demonstrate that models with a high level of accuracy are not crucial for extensive installations. Conversely, though, models with a high level of adaptability cannot be employed for applications that need a high degree of very accurate description. The next section is going to make use of multivariate research interest to provide a method for a quadratic model for EEG order based on wavelet pressure. The problems which people have expressed concern are intended to be solved by this paradigm. This model will aid in the efficient and adaptable EEG characterization of a broad range of clinical situations. It will do so by providing a framework for the analysis.

3.3 DESIGN OF THE PROPOSED MULTISPECTRAL DATA REPRESENTATION ENGINE FOR CLASSIFICATION OF EEG SIGNALS VIA ENSEMBLE MODELS

A survey of the relevant literature indicates that several different machine learning models for there have been an EEG categorization supplied; every single one of these models is employed in the process of diagnosing a particular category of brain illness. This is made abundantly clear by the many models that have been made accessible to choose from. As a consequence of this, their general-purpose classification performance is limited, and models with higher scalability performance exhibit worse accuracy, recall, and precision. In interest to get over the constraints that the aforementioned defect imposes, this part of the article introduces a more robust feature extraction engine that makes use of a quadratic classifier. This engine has a wide range of applications and may be used for several categorization tasks [180] [181] [182] [183]. The suggested model's general flow is shown in Figure 8, which may alternatively be viewed as a portrait that illustrates how the model functions internally.

Data before being processed using MFCC and iVector-based blocks, the entering EEG signals are shown to be compressed using wavelet compression.

This is done in the interest of saving space. This sequence is available for viewing. With the help of these blocks, multispectral characteristics can be extracted, leading to a more accurate representation of the input signals. These attributes are handled using a variance maximization layer to enable intelligent class-based feature selection [184] [185] [186] [187]. This layer makes an important contribution to the process as a whole. A quadratic classifier is used to identify the specified criteria of interest to complete EEG stratification into several ailment groups. This helps to ensure that the correct diagnoses are assigned to each patient. The classification of EEG data is aided by this classifier, which is made up of many neural networks and plays a part in the process. The Overall flow of the proposed model is depicted in Fig. 3.3.

It is feasible to conclude, according to the model, that one of the phases that helps with the feature diminution process is processing the incoming EEG waves via a wavelet compression block first. Equations 1 and 2 are viewed in the assessment of wavelet component extraction,

$$EEG_{a_i} = \frac{x_i + x_{i+1}}{2} \dots (1)$$

$$EEG_{d_i} = \frac{x_i - x_{i+1}}{2} \dots (2)$$

Where, $EEG_a, and\ EEG_d$ Viewed as estimated EEG & delineate EEG components dug up by the Haar wavelet transform, although $x_i \& x_{i+1}$ viewed as contemporary EEG & subsequent EEG sample values dig out from the input EEG signals. These signals are also processed via Hilbert transform, which can be observed via equation 3,

$$H_{out}(x) = 2^{\frac{j}{2}} H_{out}\left(2^j x - k\right) \dots (3)$$

Where k represents wavelet constant and to acquire final Hilbert features, the output of this model is further enhanced using equation 4,

$$f(x) = \sum_{j,k=0}^{N} EEG_a * H_{out}\,(EEG_a) \dots (4)$$

Where N viewed as several features hauled out via the Haar wavelet transform's rough components.

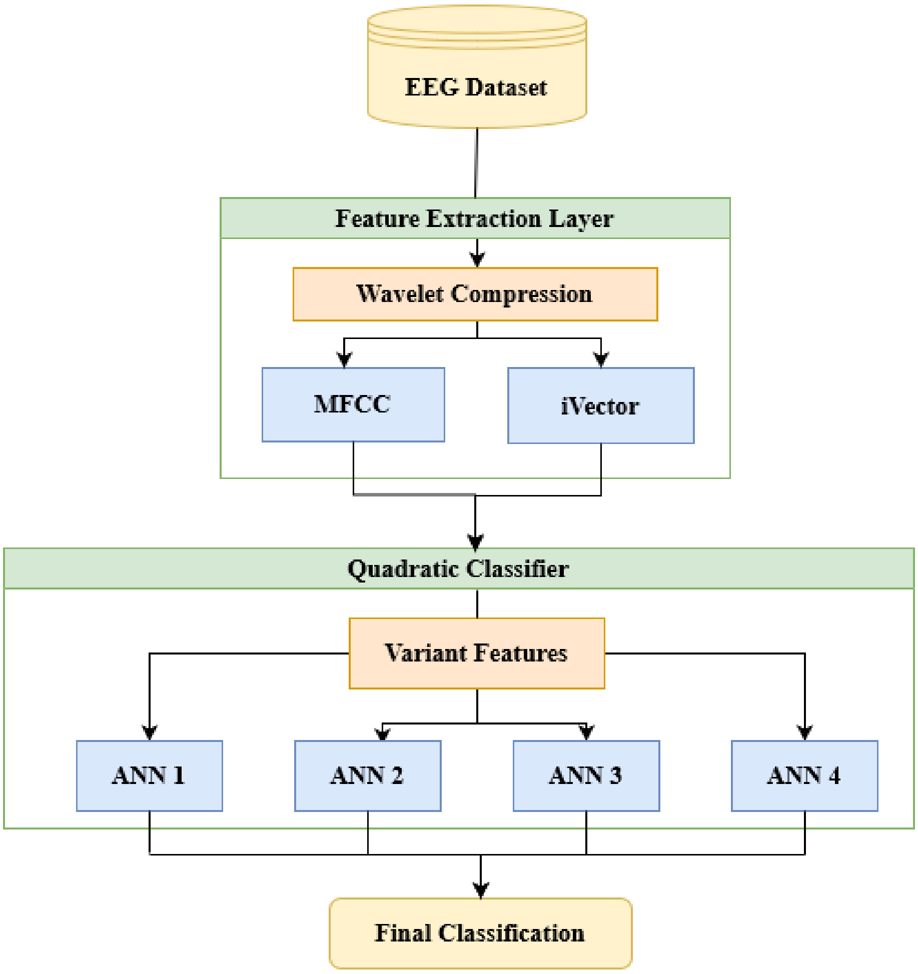

Figure 3.3 Overall flux of the proposed model

The explanatory component is thrown away as a result of the Hilbert transform, and the approximation component is what is employed for feature extraction instead. The dimensions of EEG signals are going to be shrunk by this method, but the condition of their entropy will be preserved regardless of the signal strength. These approximation components cut in half the dimensions of the input EEG data, which helps with quicker classification and provides richer feature representations [188] [189]. MFCCs are pulled out helping in the depiction of incoming signals in the frequency domain. This is done so that these components may be turned into features. In interest to carry out this activity, the Fourier transform of approximately component values is first retrieved using equation 5,

$$F_{approx\ i} = \sum_{j=0}^{N-1} EEG_{a_j} * \left[\cos\left(\frac{2 * pi * i * j}{N}\right) - \sqrt{-1} * \sin\left(\frac{2 * pi * i * j}{N}\right)\right] \ldots (5)$$

Where N represents the total number of pull-out tasters, and $i \in (0, N-1)$. Similar to Fourier, the discrete cosine components are estimated via equation 6 as follows,

$$DCT_{out} = \frac{1}{\sqrt{2N}} * C_{DCT} * \sum_{x=0}^{N-1} EEG(x) * \cos\left[(2 * x + 1) * i * \frac{pi}{2 * N}\right] \ldots (6)$$

Where, N represents the number of EEG components, while C_{DCT} is evaluated via equation 7 as follows,

$$C_{DCT} = \frac{1}{\sqrt{2}}, when\ EEG > 0, else, C_{DCT} = 1 \ldots (7)$$

Together, the Fourier, Wavelet, and DCT components fashion the final feature vector that is viewed for classification. Through the use of equation 8, these coefficients are auxiliary routed in interest to assess MFCC for spectral analysis,

$$MFCC_l = \sum_{i=1}^{n} \log(S_i) * \cos\left(\frac{pi}{n} * l * (i - 0.5)\right) \ldots (8)$$

Where, $l \in (1, n)$, n viewed as the entire count of MFCC elements that need to be dug out, S represents Mel power spectrum coefficients, and are viewed via equation 9,

$$S_i = \frac{\sum_{j=1}^{N} F_{approx\ j} * w_i}{N} \dots (9)$$

In this case, i viewed as the number of MFCC components, and Wi viewed as the weight of each MFCC component. This weight is determined by the frequency and scale value of each input signal, and it may be altered according to the needs of the model. The MFCC feature vector that was created was made by linearly combining a total of 20 distinct MFCC components that had previously been extracted. This vector has been merged with iVector features that are effective. The iVectors were computed using equation 10, and the results are as follows,

$$iVector_i = \begin{bmatrix} (1,1)_{var} & \cdots & (1,n)_{var} \\ \vdots & \ddots & \vdots \\ (n,1)_{var} & \cdots & (n,n)_{var} \end{bmatrix} * F_{approx\ i} + MAX\left(\bigcup_{j=1}^{N} F_{approx\ j}\right) \dots (10)$$

Where, N, F_{approx} viewed as number of inputs and Fourier transform of that incoming data, while $(x, y)_{var}$ Viewed as the variance between Fourier components x & y, that was assessed via equation 11 as follows,

$$(x, y)_{var} = \exp\left(\frac{x^2}{2}\right) * [2 * pi * var(y) * var(x)]^{-1} \dots (11)$$

Where, $var(x)$ is viewed as the variance of input$x$, and is employed to validate the consistency of inputs. This variance is viewed via equation 12,

$$var(x) = \sum_{i=1}^{N} \frac{\left(x_i - \sum_{j=1}^{N} \frac{x_j}{N}\right)^2}{N - 1} \dots (12)$$

Based on these identities, the incoming EEG signal is pictured into feature vectors, which is appropriate for the last categorization and analysis. MFCC and iVector component visualization graphed in Fig. 3.4 (a), and 3.4 (b) respectively, wherein the feature vectors were appraised using the same EEG data.

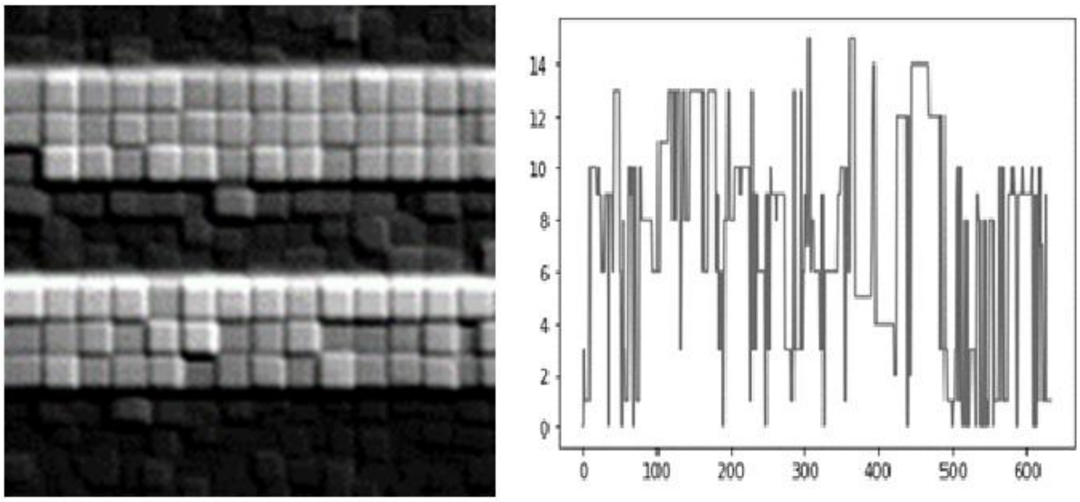

Fig. 3.4 (a) MFCC of EEG signal (b) iVector of the same signal

These features are combined to form a consolidated feature vector comprising compound feature laying-off. A fresh inter-class variance threshold is assessed between these features in interest to lessening these repetitions. This variance is viewed via equation 13, whereby the estimation of the final variance is done using information between classes.

$$V_{th} = \sqrt{\frac{\sum_{a=1}^{m}\left(FV_a - \frac{\sum_{i=1}^{m}\sqrt{\frac{\sum_{j=1}^{n}\left(FV_j - \frac{\sum_{k=1}^{n} FV_k}{n}\right)^2}{n-1}}}{m}\right)^2}{m-1}} \ldots (13)$$

There, m viewed as the total number of features in the recent class, n viewed as the total number of features in other classes, FV viewed as feature vector data for the incoming group of features. Characteristics with variance less than V_{th} are surpluses, while residuals are used for the design of the Multiple Neural Network classifier. The following is how equation 14 is viewed in finding feature variance,

$$var(F) = \sum_{i=1}^{N} \frac{\left(F_i - \sum_{j=1}^{N} \frac{F_j}{N}\right)^2}{N-1} \dots (14)$$

Where, F & N viewed as the count of the feature vector, and the total count of characteristics found in the feature vector in that order. For efficient EEG categorization, the recommended classifier uses a Quadratic Neural Network with escalating neurons, which is endowed with quality. To provide a range of output classes for the Neural Network, different layers are tied together via connections between neurons. NN models employ vast variable features to establish the final categorization. The pooled QNN model uses $n, 2*n, 3*n, \& \ 4*n$ number of neurons in the resultant classifier plan. There, n is viewed as the total number of features pulled out through variance-based collection. The final production of every NN is guarded through equation 15, wherein feature vectors, and the productivity class are created by exploiting their logarithmic ranges.

$$C_{out} = -\frac{1}{2} * \sum_{j=1}^{N} (VBF_j - \sum_{l=1}^{N} VBF_l) * \left(VBF - \sum_{i=1}^{N} VBF_i\right)^T + \log(\sum_{i=1}^{N} VBF_i) \dots (15)$$

There, $VBF, \& \ N$ viewed as haul-out variance-based features and a summed number of diverse neural network topologies were employed to resolve the classification's ultimate result. Every classifier undergoes this classification resulting in the final output class originating by the appliance of equation 16, this exploits a mode operation to coalesce an assortment of classes.

$$C_{out}^{final} = \bigvee_{i=1}^{N} C_{out_{t_i}} \ldots (16)$$

To settle on the absolute classification result, the mode maneuver prefers the class from a collection of production classes that happens with more frequency. Presentation of this association route because of precision, recall, accuracy, and delay is conferred in the text's subsequent part.

3.4 SUMMARY

In summary, the improvement in classification accuracy comes from using a mix of advanced signal processing techniques like Wavelet, Hilbert, Fourier, and Cosine transforms, which enhance the quality of feature extraction. These techniques, combined with new approaches in feature selection and classification, lead to a model that can capture complex patterns in the data with high density.

The AMVAFEx model exemplifies this approach by integrating multiple methods for feature extraction, selection, and classification. For instance, a variance-based model helps choose features with the highest variability, which minimizes redundant data and sharpens focus during classification. Additionally, MFCC (Mel-Frequency Cepstral Coefficients) and iVector methods are used to identify highly relevant features, further boosting performance.

The model's precision and recall are almost equally high, suggesting it is highly adaptable and can be applied to various EEG classification tasks effectively. This balance shows the model can accurately identify relevant patterns without sacrificing sensitivity or specificity, making it versatile for different EEG applications.

CHAPTER 4

DESIGN OF A TRANSFER LEARNING BASED BIOINSPIRED ENSEMBLE MODEL FOR PREEMPTIVE DETECTION OF STRESS & EMOTIONAL DISORDERS

"As for the future, your task is not to foresee it, but to enable it."

- Antoine de Saint Exupery

EEG signals may be used to depict stress and emotional problems via the scanning and analysis of patterns of brain wave change. The currently available EEG processing models either have a greater degree of complexity and lower accuracy levels for various illness types, or they are only appropriate for a restricted number of disorders related to stress and emotions. When applied to application-specific use cases, the performance of these models is hindered since they employ generalist Neural Network approaches for classification and post-processing. This article presents a unique Transfer Learning-based Bioinspired Ensemble Model for the Pre-emptive Detection of Stress and Emotional Diseases in the interest of addressing the problems that have been identified. In the first step of its development, the model under consideration extracts multispectral feature sets from several EEG datasets. MFCC, iVector, Cosine, Fourier, and Wavelet components are some of the characteristics that fall under this category. The goal of the GWO-based feature selection model is to maximize variance across the various stress and emotional disorder classes. This model is used to process a mixture of these characteristics across multiple datasets in interest to complete the processing [190] [191]. The decided-upon characteristics are then transformed into a two-dimensional representation and put through a CNN model for processing. This model is based on transfer learning and integrates the ResNet 101, Mobile V Net, and YoLo models. The outputs of these models' classifications are then subjected to further cross-validation via the use of ensemble classification, which is a combination of several classification models such as NB, SVM, RF, LR, and MLP. These classifiers are also used in the performance of a variety of post-processing jobs, including the determination of the likelihood of disease transmission, the estimate of future illnesses, and other similar activities. The Enterface and DEAP datasets were used to train the proposed model and then it was compared with a number of other state-of-the-art approaches in terms of its accuracy, recall, precision, AUC, and delay performance. It has been proven on the basis of this performance that the recommended model is capable of demonstrating 8.5% greater accuracy, 8.3% higher precision, 5.9% better recall, 4.5% better AUC, and 14.9% quicker classification performance, all of which make it very beneficial for clinical deployments.

4.1 INTRODUCTION TO THE TRANSFER LEARNING-BASED BIOINSPIRED ENSEMBLE MODEL

It is necessary to design multidomain processing engines that can perform the following tasks in interest to classify EEG signals into various Stress and Emotional categories. These engines must be able to pre-process EEG signals, extract useful segments, represent these segments as relevant feature sets, select highly variant inter-class feature sets from these segments, classify the selected feature sets into multiple Stress and Emotional classes, and post-process the classified data based on application-specific rules. Denoising, filtering, and cleaning the EEG signals with the use of pre-processing models is necessary in interest to discard artifacts caused by the equipment and sensor noise. In the interest of extracting meaningful chunks from wave sets such as alpha, beta, gamma, and theta, segmentation models are necessary [192]. After that, methods such as wavelet analysis, Fourier analysis, cosine analysis, long-term memory, GRU, and other forms of feature extraction are used for these sub-segments in interest to continue processing. These models make use of high-density feature sets in interest to improve feature representation. They are designed to work with certain kinds of EEG datasets & samples. These characteristics are evaluated using selection models with the hope of producing a greater degree of variation among the various groups. Fig. 4.1 depicts an example of such a model[15], which makes use of stacked LSTMs and ICA-based techniques in interest to improve both the feature representation and classification performance levels.

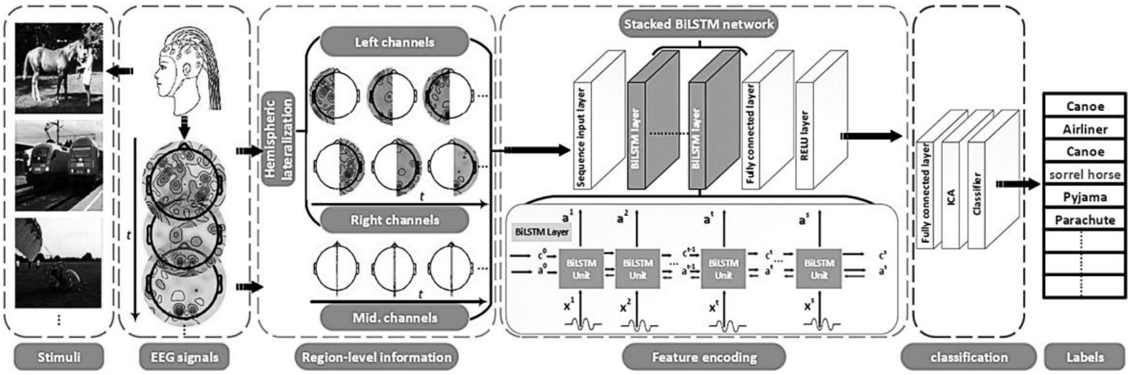

Figure 4.1 A typical EEG classification model using Stacked LSTM features

By using fully connected layers, the model can manage the classification of the retrieved attributes into one of the N stress and emotional categories. These N categories may be chosen by the user. The next chapter in this book will examine models [121] [141] [139] [122] that are comparable to one another. These models are evaluated based on the nuances that are special to the application, the advantages that are specific to the context, the limits that are specific to the deployment, and the functional future scopes. Because the existing models either have a higher degree of complexity or lower accuracy levels for a variety of types of disease, it was revealed as a consequence of this argument that they are only able to be utilized for the diagnosis of a select few Stress and Emotional disorders. This information came about as a result of the debate that took place. This is due to the constraints that are imposed by the models that are now available. Because these models depend on generic Neural Network models for classification and post-processing, their performance is impeded when they are applied to application-specific use cases. These use cases are customized to the application. This is because these models employ standard Neural Network models. One-of-a-kind Transfer Learning-based Bioinspired Ensemble Model for the Pre-emptive Detection of Stress and Emotional Disease is provided in interest to offer solutions for the issues that have been discussed. Sets in interest to provide answers to the questions that have been posed [193] [194] [195]. Section 4 examines and discusses the model's recall, AUC, delay levels, and accuracy and precision. A comparison of the model to other approaches that are considered to be the most cutting-edge in their respective sectors is also included in this research. This article concludes with numerous context-specific observations on the framework that was provided along with some suggestions for tactics that could help the model perform even better under a variety of different circumstances.

4.2 EXISTING MODELS THAT USE DEEP LEARNING FOR STRESS AND EMOTIONAL DISORDER IDENTIFICATION

To classify different kinds of stress based on EEG signals, a large number of models have been developed, and each of these models has its own set of operational properties. For instance, the research presented in [142] [143] [144] [145] [146] suggests the use of analysis of variance, k Means, and canonical correlation analysis (CCA) for the estimate of the degree of similarity between EEG signal characteristics and brain illnesses. However, these models have a poor level of accuracy and cannot be expanded to include a wider variety of disorders. The research presented in [123] suggests using a Symmetric Deep Convolutional Adversarial Network (SDCAN), which may aid in increasing classification performance for a variety of illness kinds. This can be done as a solution to this problem. Using a deep learning network that is capable of adapting to signals in real time enhances the model's accuracy and precision. Similar models are proposed in [124] [140] [125] in which the researchers discuss the use of an MSIN (Multi-Scale Inception Network), FFD (fitness for duty features), and LDSR-TL (Low-Dimensional Subject Representation-based Transfer Learning), which assisted in improving classification performance by extracting a large number of Convolutional features and then selecting them using Max Pooling layers. Similar models are also proposed in [126] [147] [148] [149]. The work further broadens these models in [150] [151] [152] which proposes the use of Kriging methods, Rapid Serial Visual Presentation (RSVP), and Shallow CNN (SCNN), which all help in improving accuracy performance by identifying redundant features and replacing them with their augmented counterparts. These models can be found in [153] [154] [155] [155]. The models that are addressed in [157] [158] [158] [160] further expand these procedures by incorporating Spatial and Temporal Matching (STM), Adaptive Thresholding, and Band Analysis. These three techniques allow context-sensitive feature extraction, which in turn improves overall classification performance when applied to real-time use cases.

Work presented in [161] [162] [163] further recommends the use of Peripheral Bio-signals, Spiking Neural Networks (SNNs), and Brain Connectivity Analysis, all of which aid in strengthening the feature representation capacities of the EEG signals which results in reducing the complexity of categorization under clinical situations. The performance of these models is poor, but they may be improved by the use of polysomnography sensors [164], KNN classifiers [165] the bi-hemispheric discrepancy model (BiHDM) [166], and repeated dataset assessments [167] all of which contribute to the reduction of classification error across a variety of illness types. Similar models are explored in [168] [169]. These models suggest the use of Dynamic Empirical CNN (DECNN), DF, and Fusion Networks, which aid in boosting classification accuracy by integration of high-density feature extraction models for clinical EEG datasets & samples. [170] [171] [171] are references. Use of PSD features [27], CNNs with Bi-LSTM for extraction of temporal and frequency features [28] Alternating Direction Method of Multipliers (ADMM) [29] and Optimal Graph coupled Semi-Supervised Learning (OGSSL) [30], which assists in enhancing classification performance via integration of multidomain features with one another, are all ways in which the feature extraction capabilities These models intend to enhance their classification performance for large-scale EEG datasets by enhancing several feature sets in the hope that this would increase their accuracy. Similar methods are discussed in [31] [32] [33] [34]. These methods propose the use of Semi-Supervised sparse low-rank regression (S3LRR), Channel-Fused Dense Convolutional Networks (CFDCN), Dynamic Time Warping (DTW), and CNN Models. These models offer support for the estimation of convolutional features from input datasets and improve their classification performance for multiple disease types. However, the majority of these models either have a greater degree of complexity and a lower level of accuracy for numerous kinds of diseases or they can only be applied to a limited number of stress-related and emotional illness classes. The next part suggests an establishing entirely novel Transfer Learning-based Bioinspired Ensemble Model for Pre-emptive Detection of Stress and Emotional illnesses. Additionally, the model was evaluated alongside a variety of state-of-the-art approaches while being applied to clinical use cases.

4.3 DESIGN OF THE PROPOSED TRANSFER LEARNING BASED BIOINSPIRED ENSEMBLE MODEL FOR PREEMPTIVE DETECTION OF STRESS & EMOTIONAL DISORDERS

Reviewing the models that identify stress and emotions using EEG signal analysis led to the discovery that these models either have a greater level of complexity and a lower level of accuracy for numerous illnesses kinds, or they are only relevant for a limited number of Stress and Emotional disease classes. Because the bulk of them also utilize generalist Neural Network models for classification and post-processing activities, their performance is limited when it is used for application-specific installations. This section addresses the construction of a unique transfer learning-based bioinspired ensemble model for proactive diagnosis of stress and emotional disorders in the interest of solving these difficulties. The model is intended for proactive detection of stress and emotional ailments. Fig. 4.2 depicts the flow of the model, and within that picture, it is possible to see that the suggested model first extracts multispectral feature sets. This can be seen in the figure. MFCC, iVector Components, Cosine Components, Fourier Components, and Wavelet Components are some examples of these. A feature selection approach based on GWO, which aims at variance maximization across distinct Stress & Emotional disorder classes, is used to process a combination of these characteristics across various emotional disorder classes.

In the proposed model as depicted in Fig. 4.3, the first stage is EMD-based noise reduction. Based on this briefly told methodology, raw EEG signals are decomposed into a set of intrinsic mode functions. In this research, by identifying and removing noise-related IMFs from the frequency and amplitude characteristics of the different IMFs obtained using this decomposition process, the de-noised EEG signals rise to a significant level concerning SNR. This enhanced SNR helps in the later stages of feature extraction and classification. After the reduction of noise, DWT is used to transform the de-noised EEG signals in interest to decompose them at different frequency bands and capture characteristics in both timestamp and frequency domains. Further, the wavelet-transformed signals will be input to a CNN to extract hierarchical features, from which it can utilize all the deep learning capabilities of the network to enhance feature representation and boost discriminative power between different emotional states. The last stage of the model is the one represented by ST-GCN, which extracts high-dimensional features from the output of the CNN. ST-GCN effectively calculates the spatial dependencies of electrodes and temporal dynamics of the EEG with a graph formed by nodes representing EEG electrodes and edges showing functional connectivity. This rich modeling of spatial-temporal relationships within the EEG data guarantees accurate and robust emotion recognition. The integration of EMD, DWT, CNN, and ST-GCN is a serious step forward in developing a system for recognizing emotions from EEG signals. Generally, it seeks to improve the accuracy and reliability within which the recognition of emotions is undertaken through the prospective.

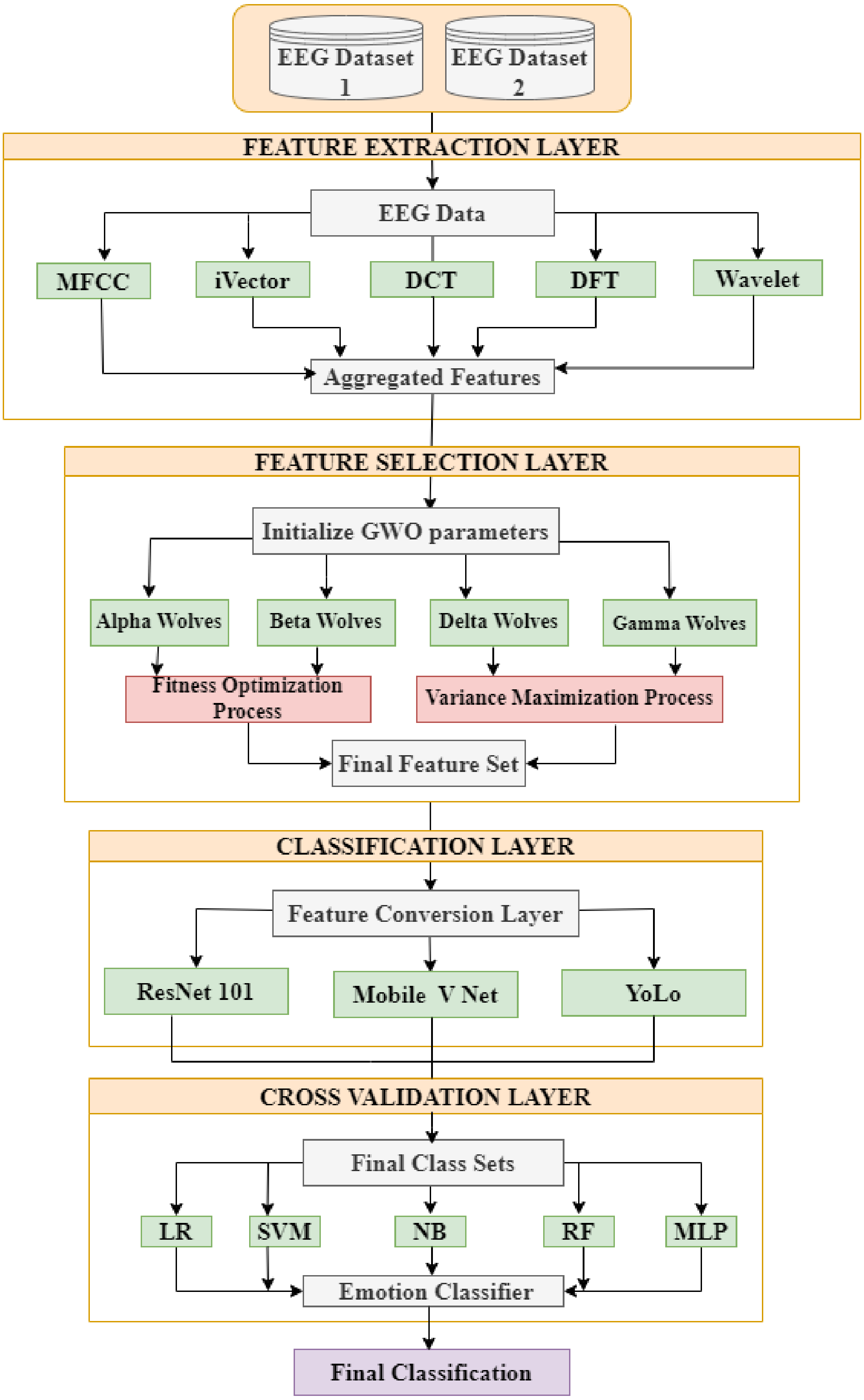

Figure 4.2 Overall flow of the proposed feature selection & classification model for different emotion types

Figure 4.3 Model architecture of the proposed classification process

The goal of this model is to reduce the amount of variation that exists across the different stress and emotional disorder classes. A Convolutional Neural Network (CNN) model is then used to process the selected characteristics when they have been processed into a two-dimensional representation. This model is based on transfer learning and integrates ResNet 101, Mobile V Net2, and YoLo techniques. The categorized outputs from these models are further cross-validated via the use of ensemble classification, which mixes models such as NB, SVM, RF, LR, and MLP for continuous accuracy enhancements [196] [197] [198] [199] [200] [201]. These classifiers are also used in a variety of post-processing tasks, such as calculating the probability that a disease will spread and predicting the sorts of diseases that may emerge in future sets.

The proposed model for emotion recognition from EEG integrates noise reduction techniques with wavelet transforms deep learning, and graph neural networks to achieve a robust and accurate system. The EEG data by itself is noisy and complex; inherently, these methods are capable of capturing the temporal and spatial dependencies. EMD will start the process with its application in noise reduction. In the process, the EMD decomposes the raw signal S(t) into a set of intrinsic mode functions Ci(t) added to a residual component r(t). The decomposition may be expressed as:

$$S(t) = \sum_{i=1}^{n} Ci(t) + r(t) \dots (17)$$

The IMFs selected, depending on their frequency and amplitude nature, are picked up for the identification and removal of noise-related components to enhance the signal-to-noise ratio sets. After this, the process of Discrete Wavelet Transform would be applied to the de-noised EEG signals. DWT decomposes the signal at different frequency bands, capturing the high and low-frequency components of the signal. Wavelet transform of a signal x(t) is defined as given below,

$$Wx(a,b) = \int_{-\infty}^{\infty} x(t)\psi * (t - ba)dt \dots (18)$$

Here, is the mother wavelet, is the scaling parameter, and is the translation parameter for this process. The coefficients obtained from this process are then used to form a multi-resolution analysis of the signal at hand. It is very useful in capturing the dynamics along the time axis of EEG signals. These high-dimensional features obtained from wavelet coefficients are supplied to a Convolutional Neural Network. The CNN uses multiple layers of convolution and pooling to obtain hierarchical features. Using mathematical expressions, the convolutional operation for the k^{th} feature map may be represented as,

$$hk = f\left(\sum_{i=1}^{M} xi * wik + bk\right) \dots (19)$$

where xi is the input signal, wik is the weight matrix, bk is the bias term, $*$ denotes the convolution operation, and f denotes the activation function. By doing so, this process gives CNN the capability to learn complex features that capture local and global patterns in data samples. These features are then extracted from the CNN to construct a graph for the Spatial-Temporal Graph Convolutional Network. In this graph, nodes are EEG electrodes; edges represent functional connectivity. The adjacency matrix A can be defined by measures of functional connectivity or anatomical distances. The graph convolution operation is given by,

$$H(l+1) = \sigma\left(D^{-\frac{1}{2}} A D^{-\frac{1}{2}} H(l) W(l)\right) \dots (20)$$

Where Hl refers to the input feature matrix at layer l, D is the degree matrix, A the adjacency matrix, Wl the weight matrix, and σ the activation function. Since this operation will be able to capture the spatial dependencies between the electrodes. Further, the ST-GCN models the temporal dynamics using temporal convolutions, which can be represented by,

$$zt = \sum_{k=0}^{K-1} \beta k \cdot x(t-k) \dots (21)$$

where zt denotes the output feature at timestamp t, βk are the temporal convolution coefficients, x(t-k) denotes an input feature at timestamp t−k, and K is the kernel size for this process. Temporal convolution may capture the dynamic changes in EEG signals over temporal instance sets. The last output of ST-GCN will be a set of emotion class labels. The class probabilities are then inferred by applying a softmax function to the final output of the ST-GCN.

$$yi = \frac{ezi}{\sum ezj} \dots (22)$$

Here, yi is the probability of i-th class and zi is the input to the softmax function. This will permit assigning emotion labels with the model based on the features the model has learned. This integrated model has not been chosen for a vain reason: it is capable of efficiently handling the shortcomings of the existing approaches. EMD adaptively reduces noise; DWT captures multi-resolution features, CNNs extract hierarchical patterns, and STGCNs model both spatial and temporal dependencies.

As can be seen in Fig. 4.2, the first step of the modeling process involves the extraction of multidomain feature sets from the input EEG datasets & samples. At the beginning of the equalizing feature extraction procedure, all EEG signals are quantized into the range of [0,1]. This helps ensure that the features are extracted correctly. In interest to carry out this activity, equation 23 is used,

$$Q_e = \frac{N_e - \min(N_e)}{\max(N_e) - \min(N_e)} \dots (23)$$

Where, $Q_e, \& N_e$ represents EEG signals in their quantized & normal states. Based on these quantized signals, MFCC is extracted via equation 24,

$$M_e = \frac{f_s}{0.25} * \log_{10}\left(1 + \frac{Q_e}{f_s}\right) \dots (24)$$

Where, M_e represents extracted MFCC for quantized signal Q_e, sampled at frequency f_s. These components are used to augment cepstrum coefficients (C_e), which are extracted via equation 25,

$$C_e = \mathrm{ifft}[\log(\mathrm{fft}[M_e])] \dots (25)$$

To remove any DC offsets, these cepstrum components are normalized ($Norm_e$) via equation 26,

$$\mathrm{Norm}_e = \frac{\left(C_e - \sum_{i=1}^{N} \frac{C_{e_i}}{N}\right) * (N-1)}{\sqrt{\sum_{j=1}^{N} \left(C_{e_j} - \sum_{i=1}^{N} \frac{C_{e_i}}{N}^{2}\right)}} \ldots (26)$$

Where, C_{e_i} represents cepstrum coefficients of input signal for the i^{th} frequency levels. The normalized signal is further filtered in interest to remove any noise levels via the triangular filtering process via equation 27,

$$T_e = \sum_{i=0}^{N-1} \left[\mathrm{Norm}_{e_i}\right]^2 * \mathrm{Mel}_{h_i} \ldots (27)$$

Where, Mel_{h_i} Represents a pre-set filter bank matrix for Mel Frequency Components. This is highly useful for the post-processing of EEG signals, and is evaluated via equation 28,

$$\mathrm{Mel}_h(i) = \frac{i - f(h-1)}{f(h) - f(h-1)} \ldots (28)$$

Where f represents the amplitude of the EEG signal for given frequency levels. Finally, the MFCC components are calculated by passing the triangular filtered signal through a Discrete Cosine Transform (DCT) process via equation 29,

$$\mathrm{MFCC}_i = \sum_{m=1}^{M} \log[T_e(m)] * \cos\left[i * \left(m - \frac{1}{2}\right) * \frac{pi}{M}\right] \ldots (29)$$

Where, i indicates the MFCC feature index, and is dependent on some frequency components which are needed to be analyzed. Based on these components, iVectors are extracted, which assist in the identification of cepstral amplitude levels for different input types. These vectors are extracted via variance calculations as indicated by equation 30,

$$\mathrm{iVector}_i = \mathrm{MAX}\left(\bigcup_{j=1}^{N} x_j\right) + \begin{bmatrix} (1,1)_{var} & \cdots & (1,n)_{var} \\ \vdots & \ddots & \vdots \\ (n,1)_{var} & \cdots & (n,n)_{var} \end{bmatrix} * x_i \ldots (30)$$

Where N represents the number of EEG samples, x represents the normalized EEG signal, while $(x, y)_{var}$ represents relative variance levels, and is estimated via equation 31,

$$(x, y)_{var} = \frac{\exp\left(\frac{x^2}{2}\right)}{2 * pi * var(x) * var(y)} \ldots (31)$$

Where, $var(x)$ indicates singular variance levels, and is estimated via equation 32 as follows,

$$var(x) = \frac{1}{N-1} * \sqrt{\sum_{i=1}^{N} \left(x_i - \sum_{j=1}^{N} \frac{x_j}{N}\right)^2} \ldots (32)$$

After variance evaluation, Fourier components are extracted for representing EEG signals into multiple domains, via equation 33,

$$F_i = \sum_{j=0}^{N-1} x_j * \left[\cos\left(2 * pi * i * \frac{j}{N}\right) - i * \sin\left(2 * pi * i * \frac{j}{N}\right)\right] \ldots (33)$$

Along with these features, wavelet components are extorted via equations 34 & 35 as follows,

$$w_{i_{approx}} = \frac{x_i + x_{i+1}}{2} \ldots (34)$$

$$w_{i_{det\,ail}} = \frac{x_i - x_{i+1}}{2} \ldots (35)$$

Where, w_{approx} represents approximate Haar wavelet component, while w_{detail} represents detailed Haar wavelet component, and $i \in (1, N)$, where N represents the number of samples present in the EEG signal. Similarly, the DCT components are extracted via equation 36, which assists in representing EEG signals into Cosine domains,

$$\mathrm{DCT} = \frac{1}{2 * \sqrt{\mathrm{N}}} \sum_{\mathrm{i}=1}^{\mathrm{N}-1} \mathrm{x_i} * \cos\left[\frac{(2 * \mathrm{i} + 1) * \mathrm{j} * \mathrm{pi}}{2 * \mathrm{N}}\right] \ldots (36)$$

All these features are combined, and given variance maximization operations are used in the GWO-based feature selection model to pick highly variable feature sets. The following procedure defines the way the model behaves:

Initially, setup following GWO parameters, which will assist in controlling its performance,

- Initialize total iterations for GWO (N_i)
- Initialize total wolves for GWO (N_w)
- Initialize the learning rate for all wolves (L_r)
- Setup all wolves as ‘Delta Wolves’
- Setup total number of aggregated feature sets (N_f), and total classes (N_c)
- Iterate through all wolves, and for each iteration perform the following tasks,
- In this iteration, if the current wolf is marked as ‘Delta Wolf’, then modify it, else skip the next wolf in sequence.

For modification, perform the following tasks,

Extract stochastic feature sets via equation 37,

$$\mathrm{f_{ext}} = \mathrm{STOCH}(\mathrm{L_w} * \mathrm{N_f}, \mathrm{N_f}) \ldots (37)$$

Where STOCH represents a Markovian stochastic process.

Based on these feature sets, evaluate inter-class variance levels via equation 38,

$$\mathrm{V_{avg}} = \sqrt{\frac{\sum_{\mathrm{a}=1}^{\mathrm{m}}\left(\mathrm{x_a} - \frac{\sum_{\mathrm{i}=1}^{\mathrm{m}} \sqrt{\frac{\sum_{\mathrm{j}=1}^{\mathrm{n}}\left(\mathrm{x_j} - \frac{\sum_{\mathrm{k}=1}^{\mathrm{n}} \mathrm{x_k}}{\mathrm{n}}\right)^2}{\mathrm{n} - 1}}}{\mathrm{m}}\right)^2}{\mathrm{m} - 1}} \ldots (38)$$

Where m represents some features in the current class, n represents the number of features in other classes.

This variance is extracted for features of each class, and based on it, Wolf fitness is evaluated via equation 39,

$$f_w = \frac{\sum_{i=1}^{N_C} V_{avg_i}}{N_c} \ldots (39)$$

Where, N_c represents the total number of classes presents in the input datasets.

This vigor is evaluated for each Wolf, and a fitness threshold is evaluated via equation 40,

$$f_{th} = \sum_{i=1}^{N_w} f_{w_i} * \frac{L_w}{N_w} \ldots (40)$$

After evaluation of this threshold, mark each wolf into a different category via the following process,

If $f_w > f_{th}$, then mark the wolf as 'Alpha Wolf'

If $f_w < L_w * f_{th}$, then mark it as 'Gamma Wolf'

If $f_w < L_w * \frac{f_{th}}{2}$, then mark it as 'Delta Wolf'

Otherwise, mark it as 'Beta Wolf'

After completing each iteration, update the wolves according to their current level of fitness.

After arriving at the final phase, select the wolf with the highest fitness levels and use its features to keep going with the classification process. These features represent maximum interclass variance and thus can be used for high-efficiency classification operations. To perform this classification, a combination of ResNet101, MobileVNet2, and YoLo models is used, which requires input data in the form of 2D arrays [202], [203] [204]. To perform this conversion, the following process is used, Initialize an empty 2D array of size 224x224, which is required by most of the CNN models.

Initialize $\mathrm{row} = 0, \mathrm{col} = 0, \& \, idx = 0$

Loop through each element in the selected feature vector, and produce the output 2D array via equation 41,

$$\mathrm{Out}_{2D}(\mathrm{row}, \mathrm{col}) = \mathrm{f}_{\mathrm{sel}}(\mathrm{idx}) \ldots (41)$$

Where, Out_{2D} represents output 2D array, while $\mathrm{f}_{\mathrm{sel}}$ represents selected features from the GWO model process.

After this assignment, increment the indices via equation 42,

$$\mathrm{idx} = \mathrm{idx} + 1,$$

$$\text{and } \mathrm{col} = \mathrm{col} + 1 \ldots (42)$$

Check if $\mathrm{c} = 224$, perform the following operations as indicated by equation 43,

$$\mathrm{col} = 0, \& \, row = row + 1 \ldots (43)$$

Repeat the process for all the selected features, and create new 2D arrays if the feature size is above 224x224

Based on this process, 2D feature vectors are generated, and processed via different CNN models for classification into different emotional disorder classes. These models initially convert all 2D vectors into convolutional features via equation 44,

$$\mathrm{Conv}_{\mathrm{out}_{i,j}} = \sum_{a=-\frac{m}{2}}^{\frac{m}{2}} \sum_{b=-\frac{n}{2}}^{\frac{n}{2}} \mathrm{Out}_{2D}(\mathrm{i} - \mathrm{a}, \mathrm{j} - \mathrm{b}) * \mathrm{LReLU}\left(\frac{\mathrm{m}}{2} + \mathrm{a}, \frac{\mathrm{n}}{2} + \mathrm{b}\right) \ldots (44)$$

Where, m, n represents window sizes of different convolutional blocks, a, b represents padding sizes which are decided by the convolutional model internal layer structures. In this case, the Leaky ReLU is used to activate convolutional features via equation 45,

$$\mathrm{LReLU}(\mathrm{x},\mathrm{y}) = \mathrm{l_a} * \mathrm{x} + \mathrm{l_b} * \mathrm{y}, \text{when } \mathrm{x} < 0 \; or \; y < 0, else \; LReLU(\mathrm{x},\mathrm{y}) \\ = \mathrm{x} + \mathrm{y} \ldots (45)$$

Where, $\mathrm{l_a}, \mathrm{l_b}$ represents hyperparameters of the LReLU model, and are tuned via a continuous accuracy evaluation process. These attributes are extracted by the ResNet101, YoLoV2, and MobileVNet2 models, which assist in recognizing highly variance feature sets. The YoLoV2 model is depicted in Fig. 4.4 as follows,

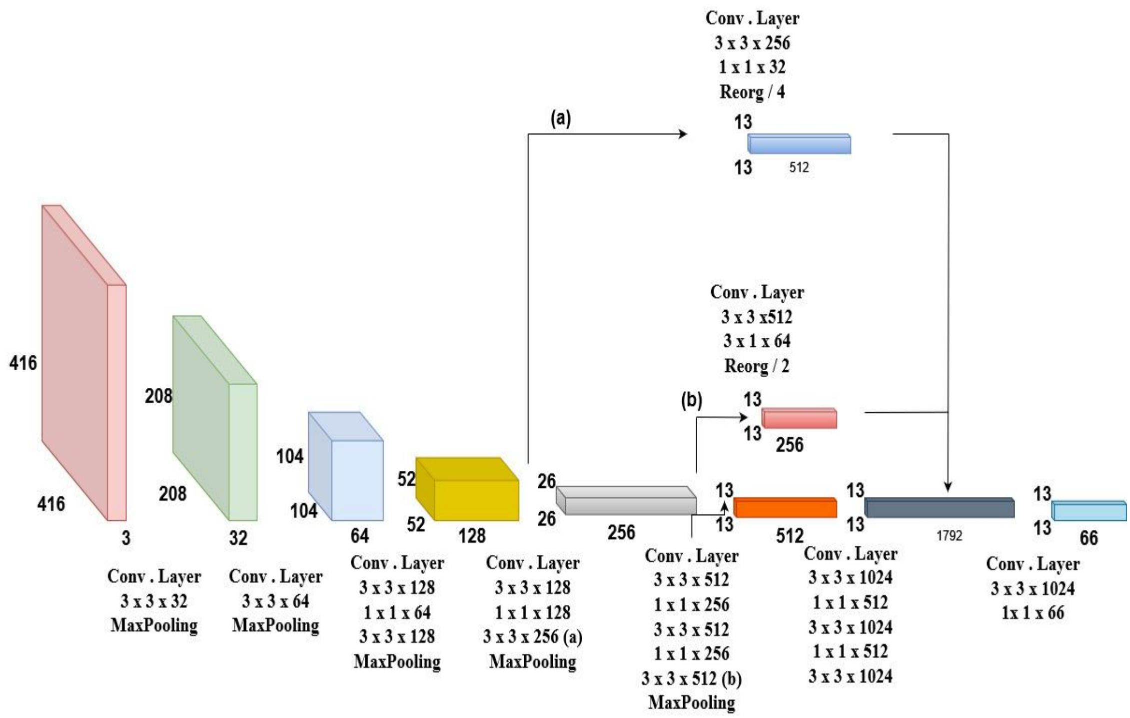

Figure 4.4 Internal design of the YoLoV2 Model

Based on Fig. 4.4, it can be observed that the maximum Variance Pooling (MaxPool) layer cascades with convolutional layers to help acquire extremely diverse Convolutional feature sets. The MaxPool layer evaluates a variance threshold via equation 46, which assists in the selection of features that have higher variance levels.

$$f_{th} = \left(\frac{1}{N_f} * \sum_{x \in N_f} x^v \right)^{1/v} \dots (46)$$

Where, N_f represents the total number of features extracted by the convolutional layer, while v represents their variance levels, which is evaluated via equation 47,

$$v = v_h * \sqrt{\frac{\left(\sum_{i=1}^{N} \left(x_i - \sum_{j=1}^{N} \frac{x_j}{N} \right)^2 \right)}{N + 1}} \dots (47)$$

Where, v_h is the MaxPool hyperparameter, and it is tuned individually by different CNN models for high accuracy performance which is similar to YoLo, the proposed model also uses ResNet101, which lends a hand in the identification of residual feature sets. The ResNet101 Model is portrayed in Fig. 4.5, wherein convolutional blocks are cascaded with different identity blocks for better feature extraction performance.

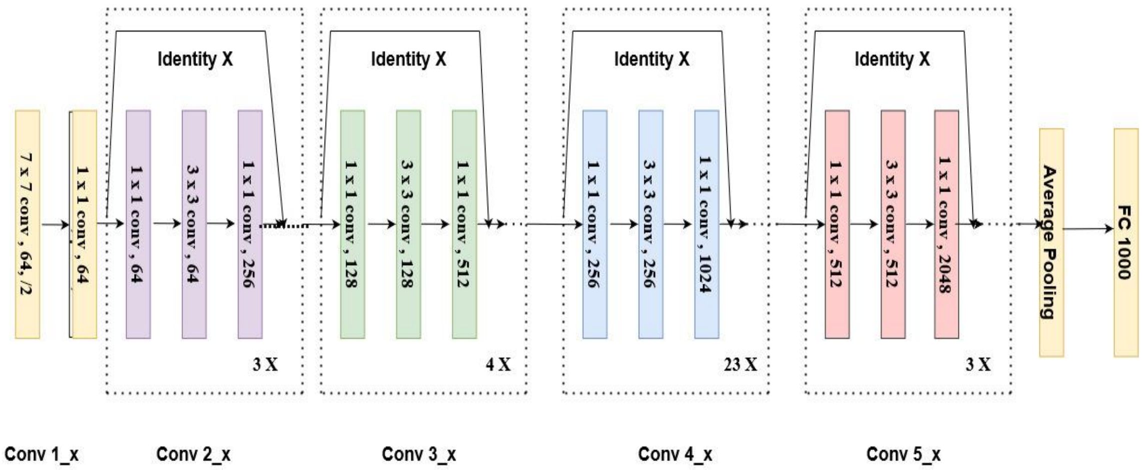

Figure 4.5 Design of the ResNet101 Model for classification of EEG signals

The identity block assists in the evaluation of variance-based feature sets, which are represented via equation 48,

$$i = var\left(x_{in} * U^i + h_t * W^i\right) \dots (48)$$

Where, x_{in}, h_t represents EEG features, and a residual kernel matrix, which is initialized by the ResNet101 model for better feature representations. The ResNet101 model is cascaded with MobileVNet2-based CNN, which is depicted in Fig 4.6 and assists in high-speed classification operations.

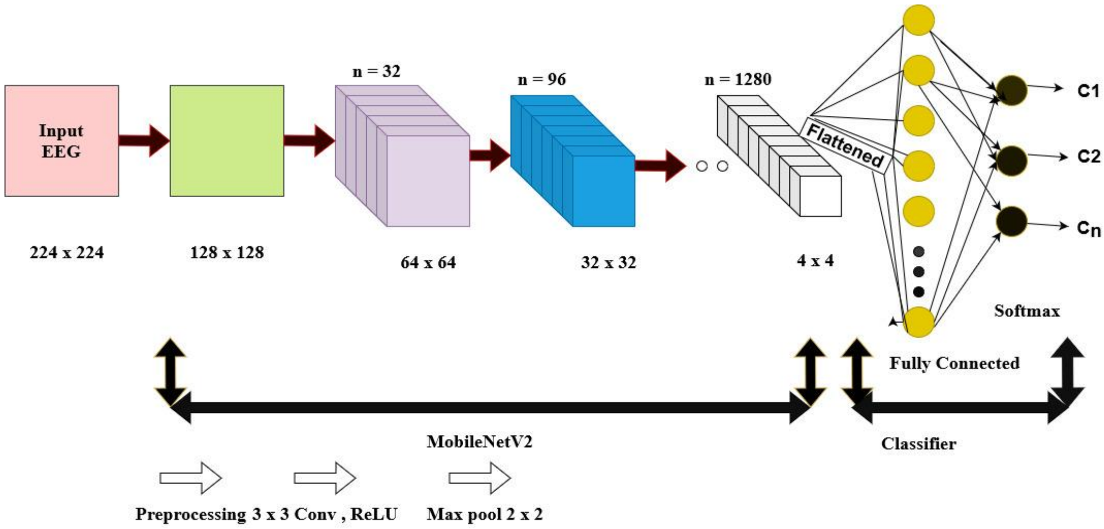

Figure 4.6 Design of the MobileVNet2 model for the high-speed classification process

Features from all the models are combined via a Purely Linear activation function for estimating final output emotion classes via equation 49,

$$C_{out} = \text{purelin}\left(\sum_{i=1}^{N} f_{out} * W_i + b_i\right) \ldots (49)$$

Where, C_{out} represents the output class, f_{out} represents output feature vectors, $W_i \& b_i$ represents weights of the Fully CNN (FCNN), and their respective bias value sets. These weights & biases are updated via hyper-parameter tuning which works via equation 50,

$$HP_{i+1} = HP_i + L_w, \text{when } Acc_i < Acc_{i+1}, \text{else}, HP_{i+1} = HP_i - L_w \ldots (50)$$

Where, HP represents hyperparameter, while Acc represents accuracy due to given hyperparameter configurations. Results of the tuned hyperparameters are cross-validated via a combination of NB, SVM, LR, RF, and MLP models [205] [206] [207]. Table 2 describes the internal parameters for each classification model as follows,

Table 4.1 Parameters used for each classification model

Method	**Parameters Used**
NB	Prior probabilities = Feature level Variances for each class Smoothing Factor = 0.5
RF	Total Estimators = Total features * Number of emotion-based diseases Split criteria = Based on entropy levels Depth of Forest = 2 Total samples used for splitting operations = Number of features / Total classes
LR	Use normalized features = No. Regression Jobs = 2 * Number of classes / Classes used on a per dataset basis
MLP	Total hidden layers = 4 Total neurons used per layer = Index of layer * Total selected feature sets ANN Mode for Classifications = Backpropagation with Feedforward operations
SVM	Gamma ranges = Max (Var) / Mean (Var) C = Min (Var) / Mean (Var)

Based on these parameters, the classification of input EEG signals is done for different emotion types, and the final class is evaluated via equation 51,

$$c_{out} = A(NB) * c(NB) + A(LR) * c(LR) + A(RF) * c(RF) + A(MLP) * c(MLP) + A(SVM) * c(SVM) \ldots (51)$$

Where, $A(i)$ represents the accuracy of the i^{th} classifier and & $c(i)$ represents the output class of the classifier which assists in ensembling these classifiers to obtain final emotion disease types. The classification accuracy of these classifiers is combined with the CNN model in interest to obtain the final disease types. Due to the combination of these models, classification performance is improved even under multiple EEG datasets. The subsequent segment of this manuscript delves into this performance and juxtaposes it with many innovative methods in diverse contexts.

The output holds four classes of stress ranging from very low stressed, low stressed, high stressed, and very high stressed. Stress is the factor that is identified from high arousal and low valence. When emotions are discovered to be negative, sad, unpleasant, and tense, the person is more likely to experience stress [208].

Stress = (Valence < 3) and (Arousal > 5)

These techniques complement one another to obtain a comprehensive, very accurate emotion recognition system. To sum up, the proposed model exploits the latest signal processing and deep learning techniques for the task of improved emotion recognition from EEG signals. EMD, DWT, CNN, and ST-GCN provide a robust framework for extracting complex information in EEG data, hence significantly improving classification accuracy and reliability.

4.3.1 Data Collection and Data Preprocessing Layer

The proposed methodology is used with two different kinds of data like the data which is obtained from medical authorities and also the data gathered from internet resources. Framework makes use of two datasets to work on which first dataset is collected from medical expertise which is EEG data gathered by using 14 electrodes named AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4 with five bands each like theta, alpha, low beta, high beta, and gamma. This data is visualized in Fig. 4.7. Data also includes the CQ value of each channel. CQ value is the quantification cycle value which is the PCR cycle number at which the sample's response curve crosses the threshold line. This figure indicates how many cycles are necessary to discover a valid signal in the sample. The second dataset is the DEAP dataset which is available on the link https://github.com/Arka95/Human-Emotion-Analysis-using-EEG-from-DEAP-dataset?tab=readme-ov-file#readme. The detail constraints of both the datasets are presented in table 4.2.

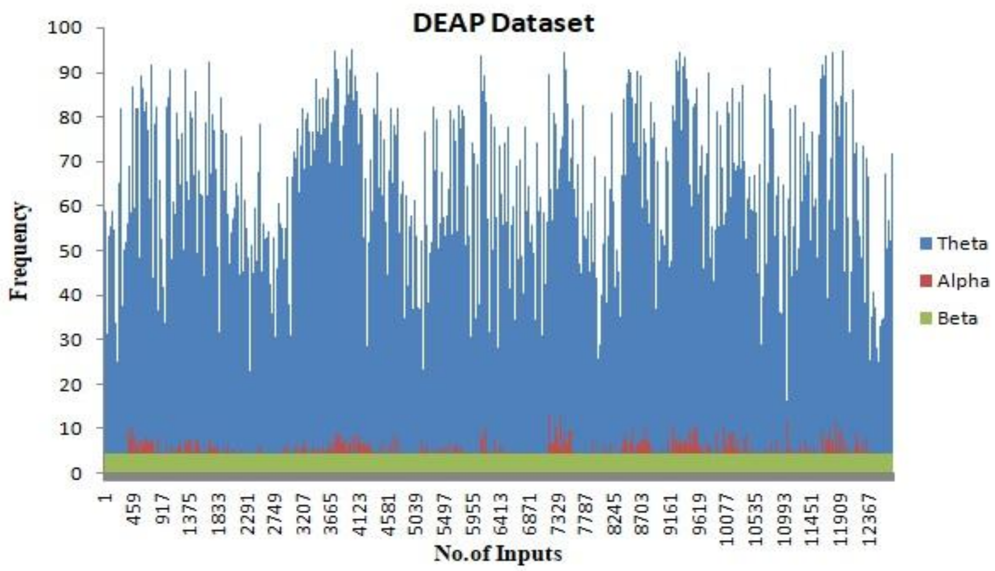

Figure 4.7 DEAP dataset visualization

Table 4.2 Comparative details of datasets

	Original Data	**DEAP Data**
Number of participants	86	32
Stimuli	Mental Mathematics	40 Number of videos
Rating scales	Arousal, Valence	Arousal, Valence, Dominance
No. of channels	14	32
No. of samples	5146	12800

The most crucial stage following data gathering is preprocessing the unprocessed data. Preprocessing in the context of EEG data entails the removal of noise and artifacts and various band separations with selection. DWT is used for preprocessing the EEG dataset.

Discrete Wavelet Transform: Image pixels can be synthesized into wavelets via the DWT technique, which can then be applied to wavelet-based coding and compression. Slow trends are maintained and high-frequency variations are eliminated from the signal with lowpass filters. An estimate of the signal is provided by the lowpass filters' outputs. Highpass filters maintain high-frequency oscillations in the signal while eliminating sluggish patterns. Highpass filters' outputs offer detailed information about the signal. The approximation coefficients and detail coefficients are defined by the outputs of highpass and lowpass filters, respectively [208] [209] [210]. The working of DWT is depicted in Fig. 4.8.

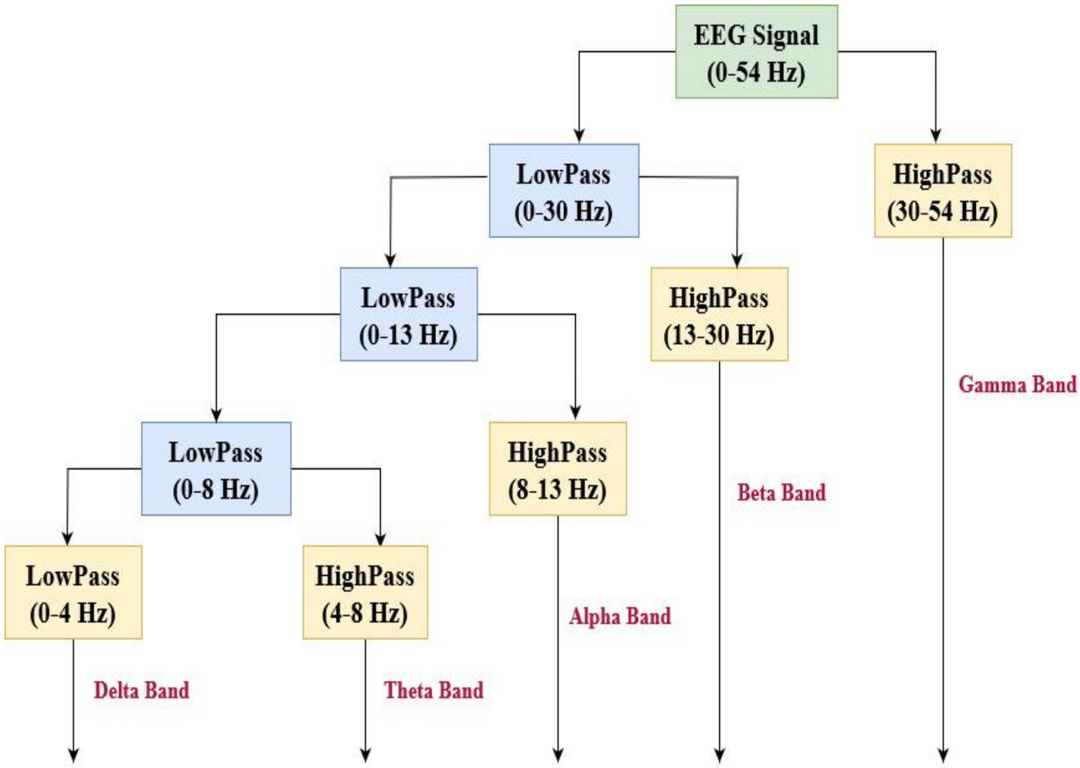

Figure 4.8 Discrete Wavelet Transform working

4.3.2 Feature Extraction Layer

The technique known as "feature extraction" involves turning raw data into numerical features so that the original data set's contents may be processed. The process begins with the extraction of multispectral feature sets from the EEG data. Numerous feature types, including MFCC, iVector, Cosine, Fourier, and Wavelet components, are included in these feature sets. Wavelet compression is used to initially compress all incoming EEG signals before MFCC and iVector-based blocks are used to process them. These building blocks aid in the multispectral feature extraction process, which improves the accuracy of the input signal representation. In an interest to help represent input signals in the frequency domain and encode these components into features, MFCCs are extracted. The MFCC feature vector is created by extracting and linearly combining the MFCC components. Incredibly effective ivector characteristics are integrated with this vector. MFCCs are those coefficients, that capture pertinent information and are widely utilized in speech and audio processing [211] [212] [213]. They represent the spectrum features of the EEG signal. A feature representation technique frequently used in speech and speaker recognition is called iVector. It is adaptable and can be used to extract pertinent data from EEG signals [214] [215] [216]. Cosine, Fourier, and Wavelet components are the mathematical methods that allow the EEG signal to be transformed into other domains, including the frequency or time-frequency domain [217] [218] [220]. These elements may all point to distinct emotional state patterns. These features are used as inputs for further analysis because they identify patterns in EEG data that are characteristic of various emotional states.

4.3.3 Feature Selection Layer

Feature selection is an approach that helps alleviate the number of data used in the model by eliminating redundant information and only using relevant data. Depending on the type of problem being addressed, it entails automatically choosing relevant characteristics for a machine learning model. GWO is employed in the feature selection procedure. Using GWO, a subset of the first retrieved features that are most useful in differentiating between various emotional disorder classifications are chosen. Maximizing the variation across these chosen features is the optimization goal [221] [221] [222]. GWO uses a routing strategy based on layers like Alpha, Beta, Delta, and Omega from highest to lowest priority depicted in Fig. 4.9 and the working is mentioned in an algorithm.

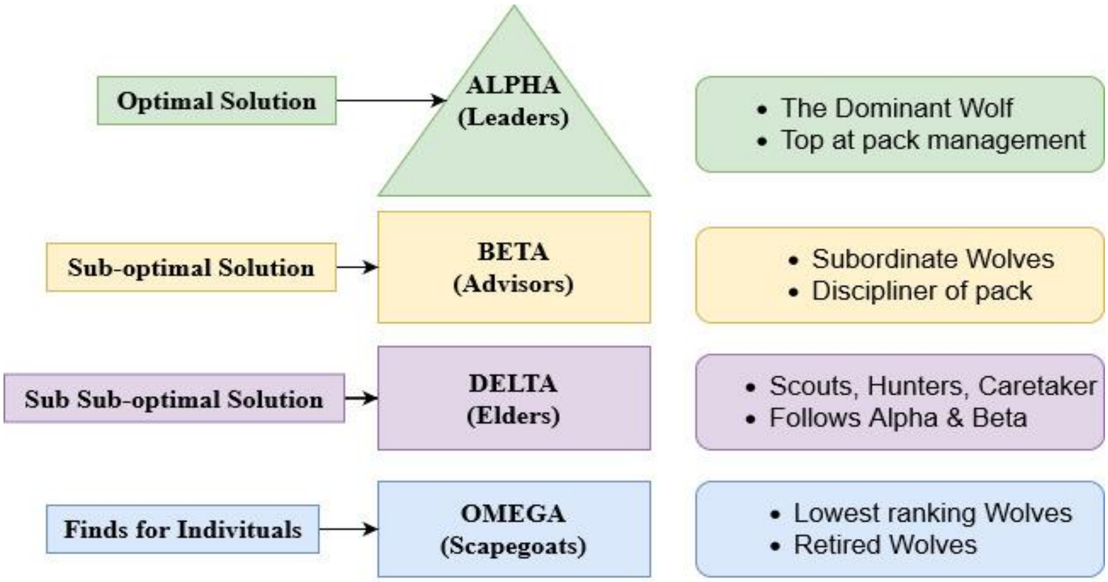

Figure 4.9 Grey Wolf Optimizer algorithm

Algorithm 1: Grey Wolf Optimizer

ALGORITHM

INPUT

N, MAX

OUTPUT

Best Position

Step 1: Initialize the random position of the wolves.

Step 2: Evaluate the Fitness function of each wolf.

Step 3: Set MAX ← Maximum no of iterations.

Step 4: While (iteration < MAX)

Step 5: Find $W\alpha$, $W\beta$, $W\delta$

Step 6: Sort in ascending manner.

Step 7: Update $W\alpha \leftarrow$ Lowest value

$W\beta \leftarrow$ Second lowest value

$W\delta \leftarrow$ Third lowest value

Step 8: for i = 1 to Ns

Evaluate $W\alpha 1 \leftarrow 2 * (W\alpha * r1 - \alpha)$

$W\beta 1 \leftarrow 2 * (W\beta * r2 - \beta)$

$W\delta 1 \leftarrow 2 * (W\delta * r3 - \delta)$

Step 9: New Position $\leftarrow (W\alpha - W\alpha 1) - (W\beta - W\beta 1) - (W\delta - W\delta 1)$

Step 10: Verify that the new position is contained within the search space perimeter.

Step 11: if (new position fitness value < current fitness value)

Update wolf Position ← New Position

Step 12: End for

Step 13: End while

Step 14: Return the value of the Best Position

Where,

α – current α position	$W\delta$ – Best position of δ
β – current β position	$W\alpha 1$ – updated position α wolf
δ – current δ position	$W\beta 1$ – updated position β wolf
$W\alpha$ – Best position of α	$W\delta 1$ – updated position δ wolf
$W\beta$ – Best position of β	r1, r2, r3 – random position values within 0 to 1.

4.3.4 Classification Layer

Soon after the final GWO iteration concludes, the wolf with the highest fitness levels is selected, and its traits are utilized for carrying out the categorization procedure. These characteristics indicate the highest interclass variance, making them suitable for very efficient classification processes. Features that are selected from the feature selection layer are then converted into 2D representation using ResNet 101, MobileV Net, and YOLO [224] [225] [226] [227] [228] [229]. Different CNN models are used to produce and process 2D feature vectors, which are then classified into various groups of emotional disorders.

4.3.5 Cross Validation Layer

The machine learning pipeline includes validation as a necessary stage. It enables us to more effectively use our data. Cross-validation allows us to obtain more metrics and make significant inferences about our data and algorithms. Finally, the data is cross-validated through the ensemble of algorithms like SVM, NB, LR, RF, and MLP which provides the output in the form of how the individual is stressed with which level.

i. Support Vector Machine

A supervised ML technique used for regression and classification problems is called SVM. SVMs perform exceptionally well for both linear and non-linear decision boundaries, and they are especially effective in high-dimensional regions. It identifies the hyperplane that optimally divides the data into distinct classes while maximizing the margin between classes is the fundamental notion behind SVM. SVMs are widely utilized in many different fields, such as bioinformatics, text classification, picture classification, and more. They have a reputation for working well in high-dimensional environments and for generalizing effectively to fresh, untested data. However, SVMs may become computationally expensive on large datasets and the choice of the appropriate kernel and tuning parameters requires careful consideration. The working of SVM is depicted in Fig 4.10.

ii. Naive Bayes

The probabilistic machine learning algorithm Naive Bayes is based on the Bayes theorem. It is extensively employed in classification tasks like spam filtering and text classification.

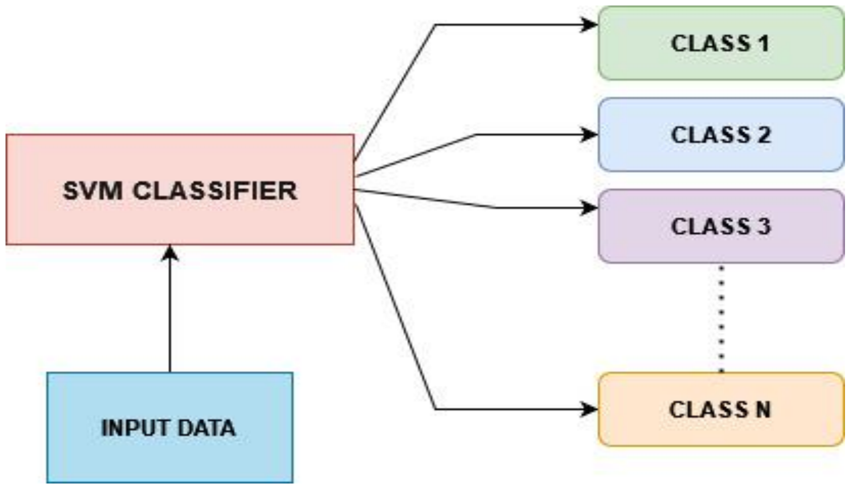

Figure 4.10 Support Vector Machine working

Despite its simplicity and certain "naive" assumptions, Naive Bayes often performs well in practice, particularly on tasks with high-dimensional data. During training, the model estimates the probabilities needed for Bayes' theorem based on the training data. In the prediction phase, the algorithm determines the class that possesses the highest probability after calculating the probability of each class for a given collection of features. Naive Bayes is computationally efficient, especially for high-dimensional data, and it can work well even with a relatively small amount of training data. While its "naive" assumption may not always reflect the true relationships between features, Naive Bayes classifiers can be surprisingly effective in practice, especially for text and document classification tasks. The working of NB is depicted in Fig. 4.11.

iii. Linear Regression

Statistically, a linear equation can be fitted to observed data using the linear regression method to represent the connection between a dependent variable and one or more independent variables. In interest to minimize the sum of squared discrepancies between the actual values and the values the model predicts, the best-fitting line must be identified. For activities like forecasting sales, linear regression is frequently utilized in many different sectors, analyzing economic trends, and understanding the relationships between variables.

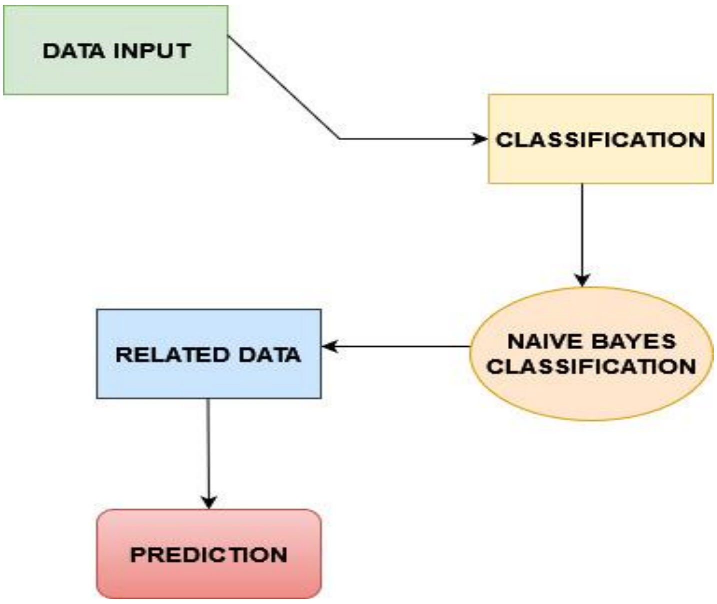

Figure 4.11 Naive Bayes working

The method assumes a linear relationship between the variables, and its effectiveness depends on the underlying assumptions being met, such as the independence of errors and homoscedasticity. The working of LR is depicted in Fig. 4.12.

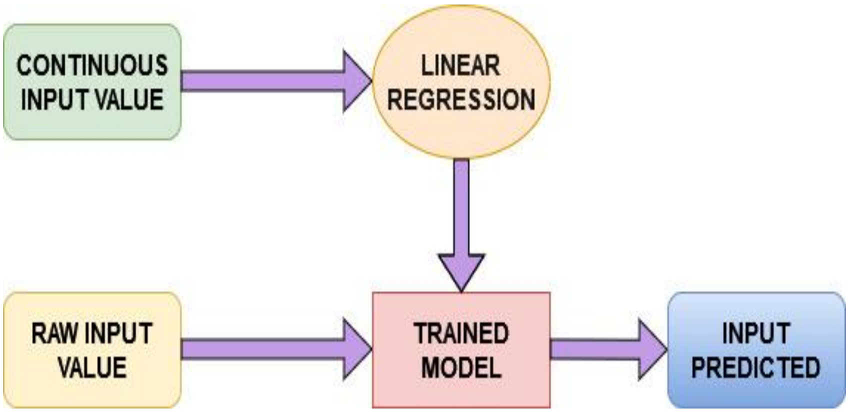

Figure 4.12 Linear Regression working

iv. Random Forest

In machine learning, Random Forest is an ensemble learning technique that is mostly applied to issues related to classification and regression. It is renowned for its exceptional accuracy and resilience and is part of the tree-based model class. Building several decision trees and combining their predictions is the basic notion underlying Random Forest, which aims to produce a more reliable and accurate outcome. Random Forests are widely used in practice due to their high performance, ease of use, and ability to handle a variety of data types. They have applications in classification, regression, feature selection, and outlier detection, among others. Popular machine learning libraries such as sci-kit-learn in Python provide implementations of RF for easy integration into machine learning workflows. The working of RF is depicted in Fig 4.13.

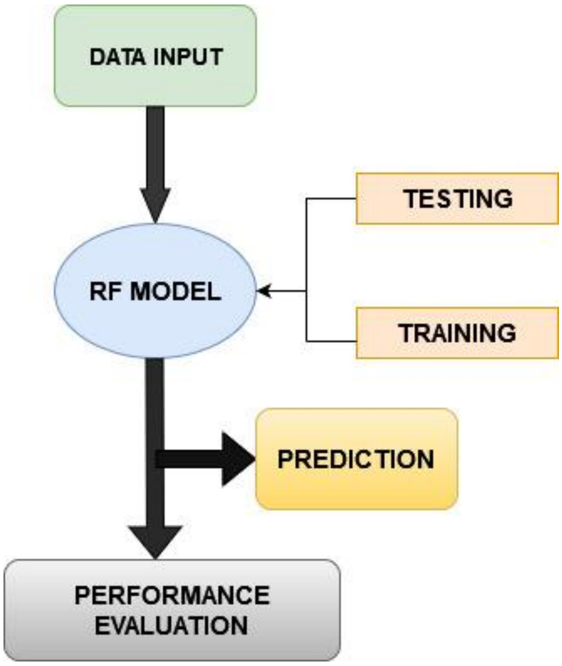

Figure 4.13 Random Forest working

v. MultiLayer Perceptron

MLP is a kind of artificial neural network used in machine learning. A computational model that draws inspiration from the functioning of biological neural networks in the human brain is known as an artificial neural network. MLPs are a particular kind of feedforward neural network, which means that data only moves from the input layer to the output layer in one way. Raining an MLP involves feeding training examples through the network, computing the output, comparing it to the true output, and adjusting the weights and biases using the back propagation technique. Usually, gradient descent and other optimization methods are used for this process. MLPs are versatile and can be applied to a wide range of tasks, including classification, regression, and pattern recognition. However, they can be sensitive to the choice of hyperparameters and require careful tuning during training. The working of MLP is depicted in Fig 4.14.

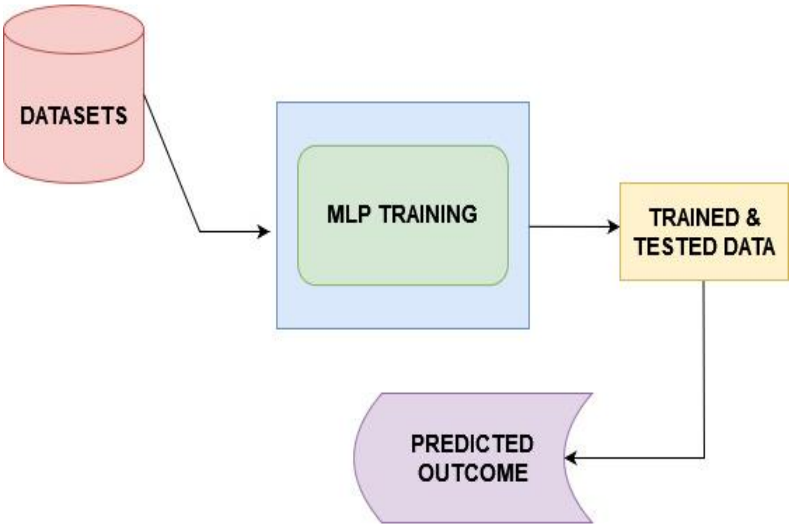

Figure 4.14 MultiLayer Perceptron working

The k-fold cross-validation technique will be used as it is the less biased method as every data will be used somewhere for training and testing [229] [230] [231]. When a classification model yields probability or confidence of the prediction in addition to the expected class, can employ measures like AUC i.e. Area under the ROC Curve [232] [233] [234]. Also, there are measure that shows the degree of mistake or accuracy of the answer like Accuracy, Precision, and Recall [235] [236] [237] [238].

4.4 SUMMARY

To summarize, this model is designed to reduce variation among different stress and emotional disorder categories, helping to classify these states more accurately. It utilizes a Convolutional Neural Network (CNN) structure with a transfer learning approach, leveraging powerful pre-trained models like ResNet 101, Mobile V Net2, and YoLo.

To improve accuracy consistently, the model uses ensemble classification, combining multiple classifiers, such as Naïve Bayes (NB), Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), and Multi-Layer Perceptron (MLP). This approach enhances the robustness of the model, as it benefits from the strengths of each classifier.

Cross-validation plays a key role here by providing additional metrics to analyze the model's performance and make meaningful insights into the data and algorithms. Ultimately, the output reveals the individual’s stress level, giving a clearer picture of their emotional state.

CHAPTER 5

RESULTS AND DISCUSSION

"Speculation and the exploration of ideas beyond what we know with certainty are what lead to progress."

– Lisa Randall

The first proposed design of a multispectral data representation engine tailored specifically for the classification of EEG signals using ensemble learning models. Ensemble models have shown promise in combining multiple classifiers to achieve higher accuracy and reliability in EEG signal classification tasks. Integrating ensemble learning with multispectral data representation aims to leverage the complementary strengths of both methodologies. The effectiveness of our proposed approach is validated through extensive experimentation on benchmark EEG datasets. Results demonstrate significant improvements in classification accuracy compared to traditional single-frequency approaches. Furthermore, the ensemble framework enhances the model's ability to generalize across different subjects and experimental conditions, crucial for real-world applications in clinical settings.

The second proposed novel approach utilizes transfer learning and bioinspired techniques to enhance the predictive capabilities of ensemble models in detecting stress and emotional disorders preemptively. By adapting pre-trained models and features extracted from bioinspired algorithms, it aims to capture nuanced patterns indicative of stress and emotional states. The efficacy of the proposed model is demonstrated through comprehensive experimentation on diverse datasets encompassing physiological, behavioral, and self-reported measures. Results indicate significant improvements in early detection accuracy compared to traditional machine learning approaches. Moreover, the bioinspired features enhance the model's interpretability and resilience to variations in individual responses and contextual factors.

5.1 PERFORMANCE STATISTICAL MEASURES

A confusion matrix serves as a gauge for the system's efficacy. Accuracy, Precision, Recall, F-score, and Delay are computed for classification models, whereas the performance of a classification model at each classification threshold is displayed on a graph which is the ROC curve. It makes use of the confusion matrix parameters like TP, FP, TN, and FN.

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Precision = TP / (TP + FN)

Recall = TN / (TN + FP)

F-score = 2 * TP / (2tp + FP + FN)

Delay and ROC Curve

5.2 RESULT OF MULTISPECTRAL DATA REPRESENTATION ENGINE FOR CLASSIFICATION OF EEG SIGNALS VIA ENSEMBLE MODELS

It has been shown that the AMVAFEx model makes use of a significant amount of neural networks to generate an accurate and definitive categorization of the EEG datasets and samples. This action was taken in interest to achieve the aimed-for outcome. As a direct result of this, this model is capable of obtaining a higher degree of accuracy, a better level of precision, and an improved level of recall in contrast to the approaches that came before it. This is because this model is more accurate and more precise levels. Utilizing a substantial number of EEG datasets, this performance was investigated to classify input waveforms into several distinct epileptic categories in interest to gain a deeper comprehension of epilepsy. These waveforms were obtained by accessing the Neuromed Epilepsy EEG Database, which is accessible at https://clinicaltrials.gov/ct2/show/NCT04647825. The database was used to gather the waveforms for research and development purposes and is made available under an open-source license. The Neuromed Epilepsy EEG Database is available under open licenses. In addition to that, there is the opportunity to have unfiltered access to these databases & samples. The EEG dataset includes 15 unique leads, all of which were utilized at some point over the step-by-step process of gathering information from 500 distinct patients. As a direct result of the results of this evaluation, it was necessary to exclude a total of 5000 one-of-a-kind objects from the dataset. After that, these objects were divided into two groups, one of which would be used for training, and the other of which would be used for testing, with a ratio of 60:40 maintained between the two groups throughout the process.

The findings of the data were compared with those that were acquired from TTFC [238], NNM [239], and LBP TH [125], and they were examined in terms of accuracy, precision, recall, and latency. This was done in interest to offer proof that the method could be depended upon; therefore that was the motivation behind it. The following are the observations that were made concerning the accuracy, and they are shown in Fig. 5.1 and Table 5.1, which can be found here. The degree of accuracy of the suggested model was shown to be 5.25 percent higher than TTFC[237] 4.3 percent higher than NNM [238] and 6.75 percent higher than LBP TH [125] for the different kinds of EEG datasets & samples. Find Fig. 5.1 in this precise place.

The most important factor contributing to this improvement in accuracy is the use of transforms such as Wavelet, Hilbert, Fourier, and Cosine, together with breakthroughs made in feature selection and classification. Other elements that contribute include the following. Because of this, the model's feature representation capabilities are increased when combined with the MFCC and iVector features, which eventually leads to better accuracy performance. The performance of classification was able to be significantly improved in this particular instance by the usage of a convolutional neural network. This was rendered possible through the network's high-density feature representation capability.

Table 5.1 Accuracy of distinct comparing models

Number of EEGs	**A (%)**	**A (%)**	**A (%)**	**A (%)**
	TTFC [238]	**NNM** [239]	**LBP TH** [125]	**AMV AFEX**
227	76.36	78.28	77.05	81.29
455	80.19	81.1	79.44	84.47
682	82.01	82.37	80.63	85.97
909	82.72	83.48	81.9	87.05
1136	84.23	85.35	83.57	88.83
1364	86.46	86.61	84.57	90.4
1591	86.76	86.91	84.86	90.72
1818	87.06	87.21	85.31	91.08
2045	87.37	88.16	86.32	91.88
2273	88.97	89.43	87.47	93.28
2727	89.88	90.34	88.35	94.24
3182	90.8	91.25	89.25	95.19
3636	91.71	92.17	90.14	96.15
4091	92.63	93.08	91.04	97.1
4545	93.55	94	91.93	98.06
5000	94.46	94.91	92.82	99.01

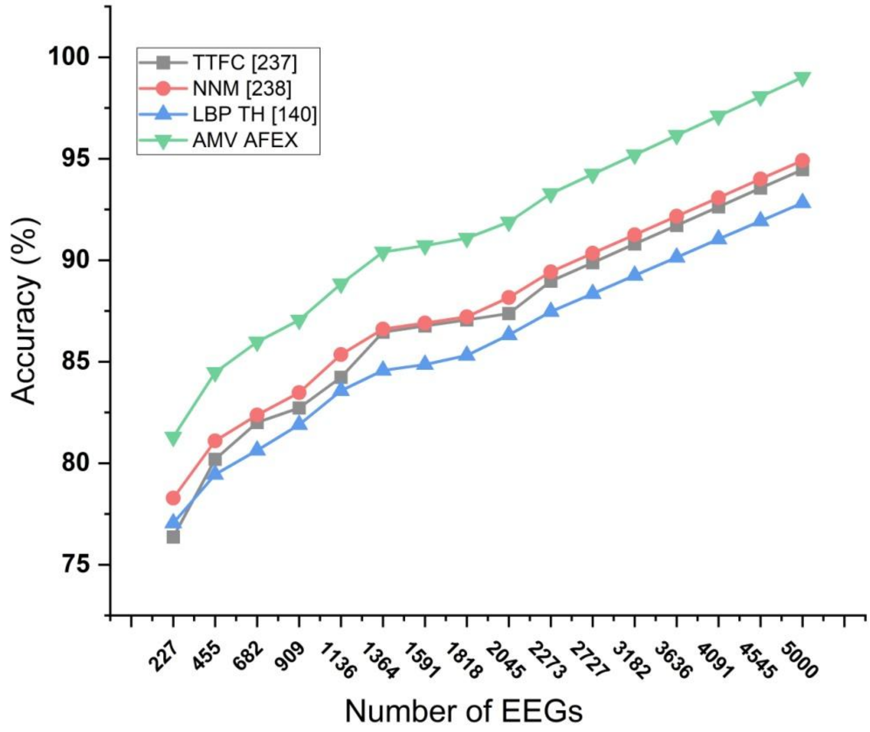

Figure 5.1 Accuracy of different models

To attain this level of performance, multiple neural networks had to be utilized in addition to the coupling of MFCC and iVector characteristics. Because of this, the categorization process was able to be carried out quite quickly. In the same vein, Table 5.2 and Fig. 5.2 can be used to assess the reliability and performance of these models.

Based on this investigation, it could be achieved to prove that, for a wide variety of EEG signal types, the proposed framework is more accurate than TTFC[237] 4.95 percent more accurate than NNM [238], and 2.9 percent more accurate than LBP TH [125]. The adoption of an extensive variety of feature extraction algorithms, together with recent advancements in selection and classification, is the primary factor contributing to this accuracy gain.

Table 5.2 Precision of distinct comparing models

Number of EEGs	**Pc** **TTFC** [238]	**Pc** **NNM** [239]	**Pc** **LBP TH** [125]	**Pc** **AMV AFEX**
227	73.63	73.96	75.41	77.47
455	76.81	76.45	78.04	80.64
682	78.28	77.62	79.34	82.12
909	79.14	78.75	80.45	83.09
1136	80.75	80.44	82.09	84.79
1364	82.42	81.52	83.31	86.41
1591	82.7	81.8	83.61	86.71
1818	82.99	82.15	84	87.04
2045	83.59	83.09	84.86	87.73
2273	84.95	84.23	86.07	89.11
2727	85.82	85.09	86.95	90.03
3182	86.69	85.95	87.83	90.94
3636	87.57	86.82	88.71	91.86
4091	88.44	87.68	89.59	92.77
4545	89.3	88.54	90.48	93.68
5000	90.17	89.4	91.35	94.6

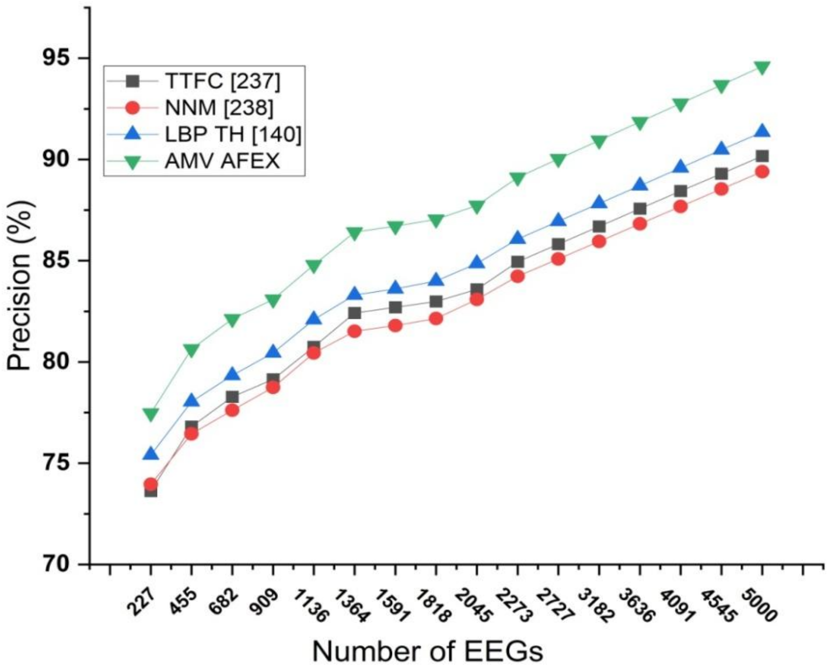

Figure 5.2 Precision of distinct models

As this is coupled with the MFCC and iVector characteristics, the model's ability to represent features is enhanced, which also improves the accuracy performance of the model. The total classification performance improved when a CNN was used, as it was in this instance. This was brought about by CNN's ability to depict features at a high density. Apart from the combination of MFCC and iVector properties, the use of MNN was essential to achieving such performance levels. Because of this, the categorization process was able to be carried out quite quickly for different use cases. Tabled in Fig. 5.3 and Table 5.3 is a comparison of how well various models perform in terms of recalling information sets.

On the foundation of this evaluation, it can be revealed that the proposed model has a recall that is 5.3 percent greater than TTFC [238], 3.9 percent higher than NNM [239], and 4.5 percent higher than LBP TH [125] for a variety of EEG datasets and samples. These results can be found in [4, 5] and [9] respectively.

Table 5.3 Recall of distinct comparing models

Number of EEGs	**Rc** **TTFC** [238]	**Rc** **NNM** [239]	**Rc** **LBP TH** [125]	**Rc** **AMV AFEX**
227	74.99	76.12	76.23	79.38
455	78.50	78.77	78.74	82.55
628	80.14	79.99	79.98	84.04
909	80.93	81.11	81.17	85.07
1136	82.50	82.89	82.83	86.81
1364	84.44	84.06	83.94	88.41
1591	84.73	84.36	84.23	88.71
1818	85.02	84.69	84.66	89.06
2045	85.48	85.63	85.59	89.81
2273	86.96	86.83	86.77	91.20
2727	87.85	87.72	87.66	92.13
3182	88.75	88.61	88.55	93.07
3636	89.64	89.50	89.43	94.00
4091	90.53	90.38	90.31	94.94
4545	91.43	91.26	91.20	95.87
5000	92.31	92.15	92.08	96.81

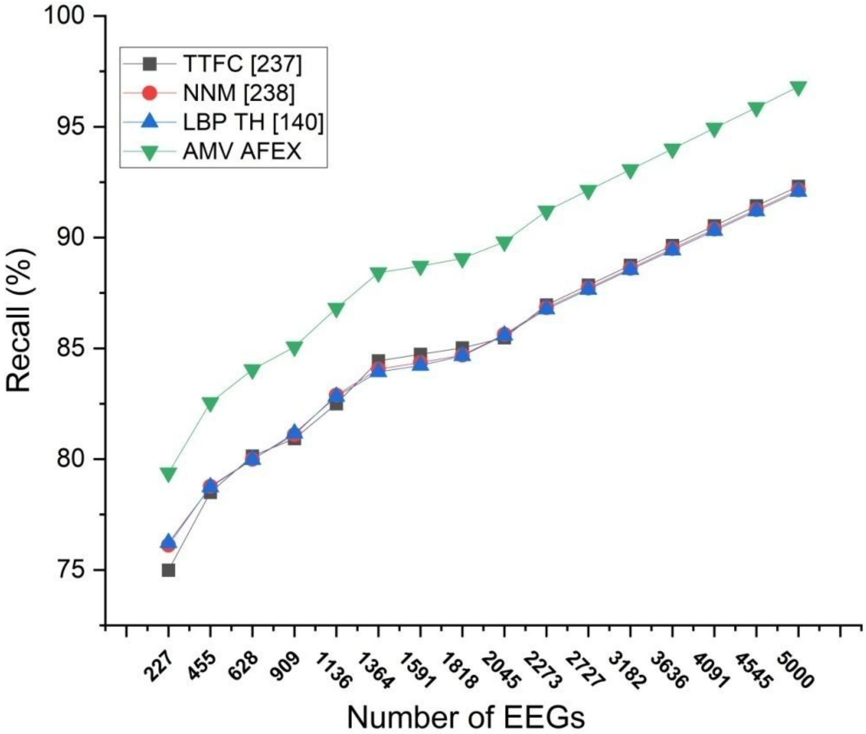

Figure 5.3 Recall of distinct models

The combination of several different feature extraction transforms, such as Wavelet, Fourier, Hilbert, and Cosine, in addition to developments in selection and classification is the key factor that contributed to this rise in recall. When paired with the MFCC and iVector features, the model's ability to represent features is enhanced as a result, the model's recall performance is boosted. The use of a Convolutional Neural Network, which was applied in this case, increased the overall classification performance. This was due to the CNN's capability of representing features in a high density. In addition to the coupling of MFCC and iVector characteristics, the use of MNN was essential to achieving such performance levels. Because of this, the categorization process was able to be carried out at high-speed levels.

Figure 5.4 and Table 5.4 present a tabular representation of the average delay required for the classification of a single EEG signal waveform. This value can be used to infer that, for the various types of EEG signals, the suggested framework has a delay that is 6.1 percent less than that of TTFC [237] 4.9 percent less than that of NNM [238], and 5.5 percent less than that of LBP TH [125]. This information can be found in the table below. The key contributor to the reduction in length of this delay was the implementation of low-complexity classifier operations and variance-based feature selection. This allowed for the shorter duration of the delay. Combined with the MFCC and iVector capabilities, these advancements improve the model's feature-describing capability and reduce computation time.

The use of a CNN, as was done in this situation, was able to contribute to an improvement in classification performance. This was possible as a result of the CNN's capacity to both represent high-density features and eliminate duplicate information. This was enabled by the application of wavelet transformations in conjunction with a variance-based feature selection methodology. Discovering the most variable features could be improved by a variance-based feature selection approach, which could subsequently reduce duplication in the output feature sets. The wavelet transform can minimize duplication in output feature sets by reducing the size of the feature vector by up to fifty percent. This performance enhancement has placed the proposed model in a position where it can be utilized in an extensive range of real-time clinical applications.

Table 5.4 Delay of distinct comparing models

Number of EEGs	**Dl** **TTFC** [238]	**Dl** **NNM** [239]	**Dl** **LBP TH** [125]	**Dl** **AMV AFEX**
227	0.45	0.44	0.44	0.42
455	0.87	0.86	0.87	0.83
628	1.27	1.27	1.27	1.21
909	1.68	1.68	1.68	1.60
1136	2.06	2.05	2.05	1.96
1364	2.41	2.42	2.43	2.31
1591	2.81	2.82	2.83	2.69
1818	3.20	3.21	3.21	3.05
2045	3.58	3.58	3.58	3.40
2273	3.91	3.92	3.92	3.73
2727	4.65	4.66	4.66	4.42
3182	5.36	5.37	5.37	5.11
3636	6.07	6.08	6.08	5.79
4091	6.76	6.78	6.78	6.44
4545	7.44	7.45	7.45	7.09
5000	8.10	8.12	8.12	7.73

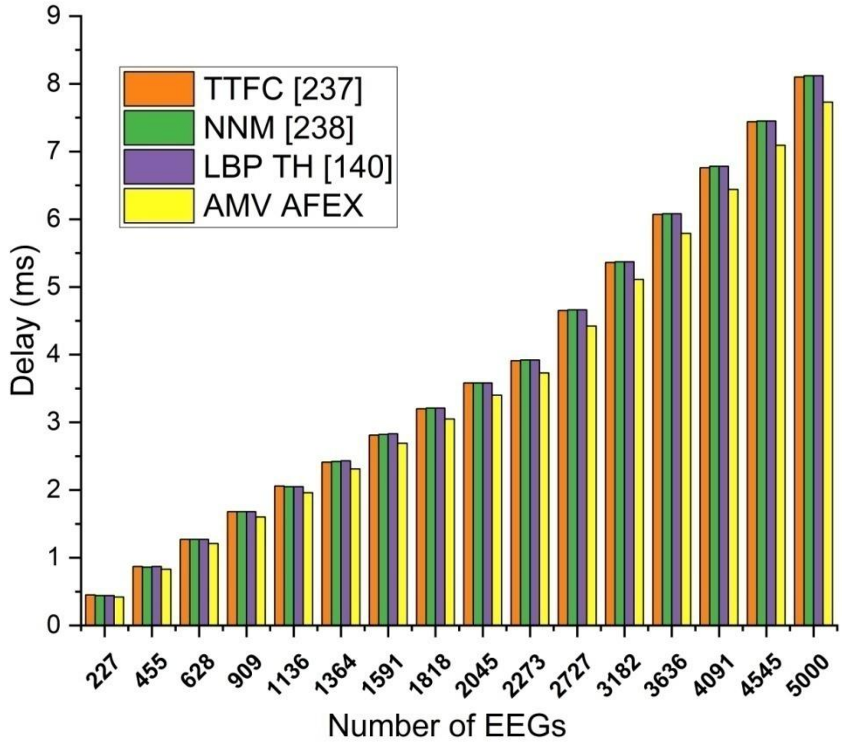

Figure 5.4 Delay performances of different models

5.2.1 Conclusion

In an interest to attain superior performance to that of currently available models, the AMVAFEx model that was demonstrated combines several kinds of techniques to perform feature extraction, selection, and classification. Although the variance-based model assists in selecting features with the greatest variation, which helps minimize repetition during the classification phases, the MFCC and iVector techniques aid in the evaluation of highly relevant features. The given features are classified using a quadratic mode MNN classifier. This classifier contributes to high accuracy, high recall, and extremely accurate classification. When compared to several other models that are considered to be state-of-the-art, it was found that the suggested model can improve the accuracy of the categorization. Because of this, the model that was suggested may be used in clinical settings that need a high level of accuracy. It was discovered that the suggested model had an accuracy that was over 5% higher than TTFC [238], over 4% higher than NNM [239], and over 6% higher than LBP TH [125] for the various kinds of EEG signals. Precision and recall were shown to have almost the same levels of performance, which indicates that the model is very adaptable to a broad range of possible EEG classification applications. In addition to this improvement in performance, the model that has been suggested also demonstrates a decrease in latency. The primary rationale for this is the fact that reduction was implemented using variance-based optimizations. Consequently, for different types of EEG signals, the latency of the proposed model is 5.5% lower than that of LBP TH [125] 4.9% lower than that of NNM [238], and 6.1% lower than that of TTFC [237]. In the future, a range of EEG datasets will be available for researchers to assess the performance of the suggested model, enabling them to ascertain the model's scalability. Additionally, for better survival in a variety of brain illnesses, researchers can combine deep learning models such as recurrent neural networks with LSTM and GRUs.

5.3 RESULT OF TRANSFER LEARNING BASED BIOINSPIRED ENSEMBLE MODEL FOR PREEMPTIVE DETECTION OF STRESS & EMOTIONAL DISORDERS

Efficiency classification of EEG signals requires the design of highly efficient feature representation & classification modules, which assist in categorizing input datasets into 1 of N classes. This section compares the classification of the proposed model with the work defined in SCNN [100], DE CNN [117], and CF DCN [240], under different emotion classes. Datasets for evaluating these models were collected from the following sources,

DEAP Dataset, which is available at https://www.eecs.qmul.ac.uk/mmv/datasets/deap/. The dataset was split up in the ratio 65:20:15, with 65% of the entries used for training, 20% for testing, and the remaining 15% for cross-validation using ensemble classifiers. Considering this assessment approach, classification accuracy for different disease types was calculated via equation 46,

$$A_c = \frac{E\_C}{E_T} \ldots (46)$$

Where, E_C&E_T represents EEG records that were correctly classified, and the total number of EEG records that were used for evaluation purposes. This accuracy was evaluated w.r.t. NTEs, and can be observed from Table 5.5 as follows,

Table 5.5 Accuracy of classification for different emotional disease types

NTEs	**Ac SCNN [100]**	**Ac DE CNN [117]**	**Ac CF DCN** [240]	**Ac TLBE MSE**
5k	84.06	80.68	78.45	86.85
15k	85.51	82.16	79.85	88.4
25k	85.66	83.42	80.52	89.15
35k	85.97	84.03	80.96	89.63
45k	86.57	84.94	81.67	90.42
55k	86.84	85.58	82.1	90.89
66k	87.22	86.53	82.73	91.59
75k	87.52	87.2	83.18	92.09
90k	87.97	88.18	83.87	92.85
115k	88.4	89.17	84.56	93.6
135k	88.7	89.83	85.02	94.1
150k	88.99	90.49	85.48	94.61
168k	89.14	90.82	85.71	94.86
184k	89.29	91.14	85.94	95.11
200k	89.44	91.47	86.17	95.36

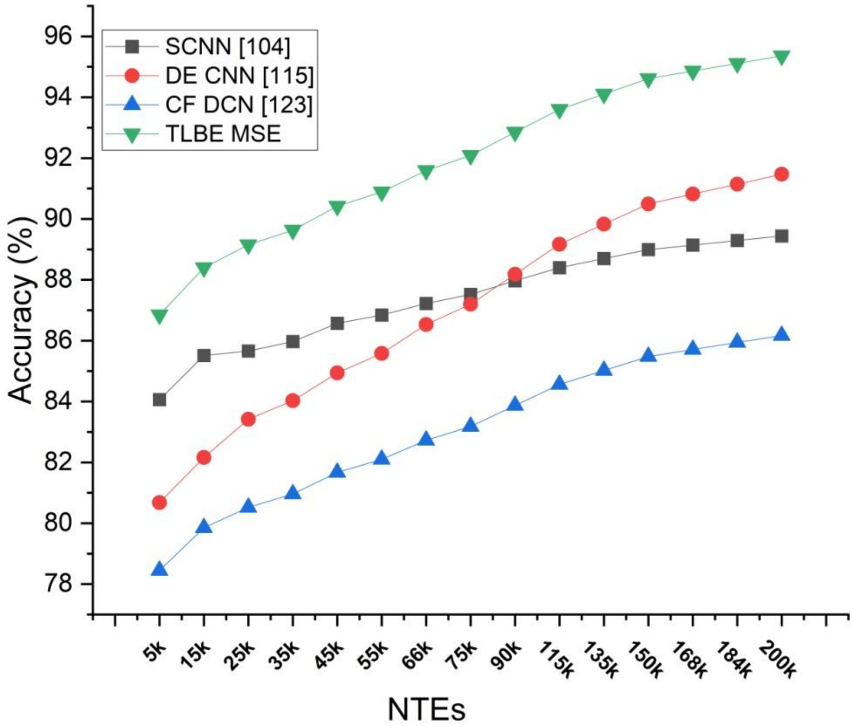

Figure 5.5 Accuracy of classification for different emotional disease types

Due to the integration of multiple feature extraction models with bioinspired feature selection & multiple models for classifications, when compared to different methods, the proposed framework may boost classification accuracy. Figure 5.5 provides validation for showing that the suggested framework outperforms SCNN [100] DE CNN [117] and CF DCN [239] by 5.9%, 3.5%, and 9.2%, respectively, in various disease scenarios. Based on a similar strategy, the precision of classification (P_c) is evaluated via equation 47, and tabulated in Table 5.6 as follows,

$$P_c = \frac{R_{CI}}{R_T} \ldots (47)$$

Where, R_{CI} &R_T represents the total number of correctly classified EEG entries, which were categorized into incorrect groups, and the total number of entries used for the classification process. These results can be observed from the following Fig. 5.6 as follows,

Table 5.6 Precision of classification for different emotional disease types

NTEs	**Pc SCNN [100]**	**Pc DE CNN [117]**	**Pc CF DCN** [240]	**Pc TLBE MSE**
5k	79.88	79.07	77.67	83.38
15k	81.25	80.53	79.05	84.86
25k	81.38	81.76	79.72	85.58
35k	81.67	82.34	80.16	86.05
45k	82.24	83.22	80.87	86.82
55k	82.47	83.87	81.3	87.29
66k	82.84	84.82	81.93	87.97
75k	83.13	85.45	82.37	88.44
90k	83.57	86.4	83.05	89.15
115k	83.97	87.38	83.71	89.86
135k	84.32	88.1	84.23	90.42
150k	84.71	88.84	84.78	91.02
168k	84.91	89.21	85.07	91.32
184k	85.11	89.59	85.35	91.62
200k	85.29	89.94	85.61	91.95

Due to the integration of multiple feature extraction models with bioinspired feature selection & multiple models for classifications, the proposed model is capable of improving classification precision when compared with other methods. This can be confirmed from Table 5.6, wherein it is observed that the proposed model is 6.5% more precise than SCNN [100], 1.9% more precise than DE CNN [117], and 5.9% more precise than CF DCN [240] under different disease scenarios.

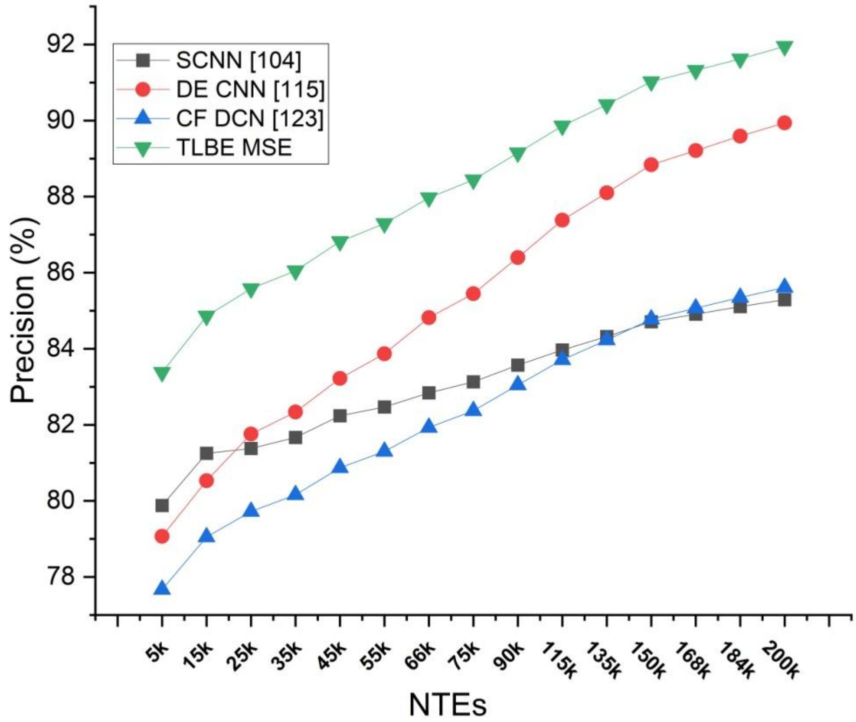

Figure 5.6 Precision of classification for different emotional disease types

This is possible due to the integration of multiple Neural Network models that assist in improving the consistency of the classification process. Similarly, the recall of classification (R_c) is evaluated via equation 48 as follows,

$$R_f = \frac{R_{CC}}{R_T} \dots (48)$$

Where, R_{CC} and R_T represents the total number of correctly classified entries that belong to correct emotion types, and the total number of entries used during the classification process. These results are tabulated in Table 5.7, wherein recall of the proposed model is compared with other reference models.

Table 5.7 Recall of classification for different emotional disease types

NTEs	**Rc SCNN [100]**	**Rc DE CNN [117]**	**Rc CF DCN** [240]	**Rc TLBE MSE**
5k	65.56	72.61	65.03	81.06
15k	66.7	73.93	66.18	82.51
25k	66.81	75.08	66.75	83.2
35k	67.06	75.62	67.11	83.65
45k	67.52	76.44	67.72	84.39
55k	67.72	77.02	68.08	84.82
66k	68.02	77.87	68.62	85.49
75k	68.27	78.45	69	85.97
90k	68.63	79.35	69.55	86.68
115k	68.86	80.25	70.11	87.38
135k	68.94	80.92	70.55	87.93
150k	69.2	81.59	71.02	88.5
168k	69.37	81.93	71.25	88.79
184k	69.55	82.28	71.49	89.08
200k	69.75	82.6	71.71	89.36

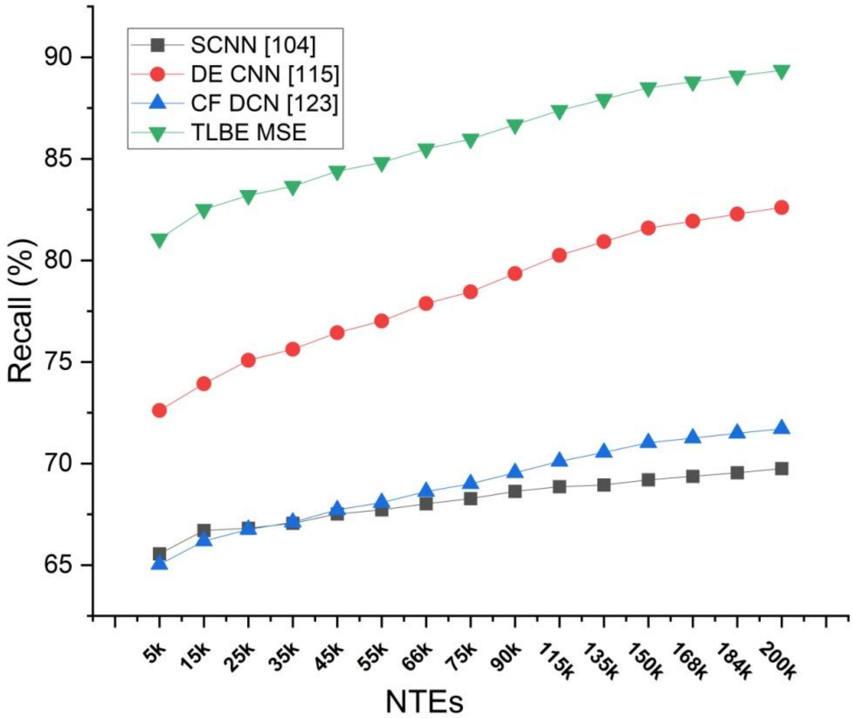

Figure 5.7 Recall of classification for different emotional disease types

Due to the integration of multiple feature extraction models with bioinspired feature selection & multiple models for classifications, the proposed model is capable of improving classification recall when compared with other methods. This can be confirmed by Fig. 5.7, wherein it is observed that the proposed model has 19.5% higher recall than SCNN [100], 6.5% higher recall than DE CNN [117], and 15.5% higher recall than CF DCN [240] under different disease scenarios. This is possible due to the integration of multiple Neural Network models that assist in improving the consistency of the classification process. Based on similar evaluations, the delay needed for the classification of different EEG signals is tabulated in Table 5.8, wherein different models along with their approximate delay values can be observed for a similar number of validation events,

Table 5.8 Delay needed for classification of different emotional disease types

NTEs	**Dl** **SCNN [100]**	**Dl** **DE CNN [117]**	**Dl** **CF DCN** [240]	**Dl** **TLBE MSE**
5k	7.71	8.11	7.59	6.17
15k	7.85	8.26	7.72	6.28
25k	7.86	8.39	7.79	6.33
35k	7.89	8.45	7.83	6.36
45k	7.95	8.54	7.9	6.42
55k	7.97	8.61	7.94	6.45
66k	8	8.7	8	6.5
75k	8.03	8.77	8.05	6.54
90k	8.07	8.87	8.11	6.59
115k	8.11	8.96	8.18	6.65
135k	8.15	9.04	8.23	6.69
150k	8.18	9.12	8.28	6.73
168k	8.2	9.16	8.31	6.75
184k	8.22	9.19	8.33	6.78
200k	8.24	9.23	8.36	6.8

The proposed model extracts a selective number of feature sets, which allows it to reduce the number of classification steps & iterations needed for the identification of emotional diseases.

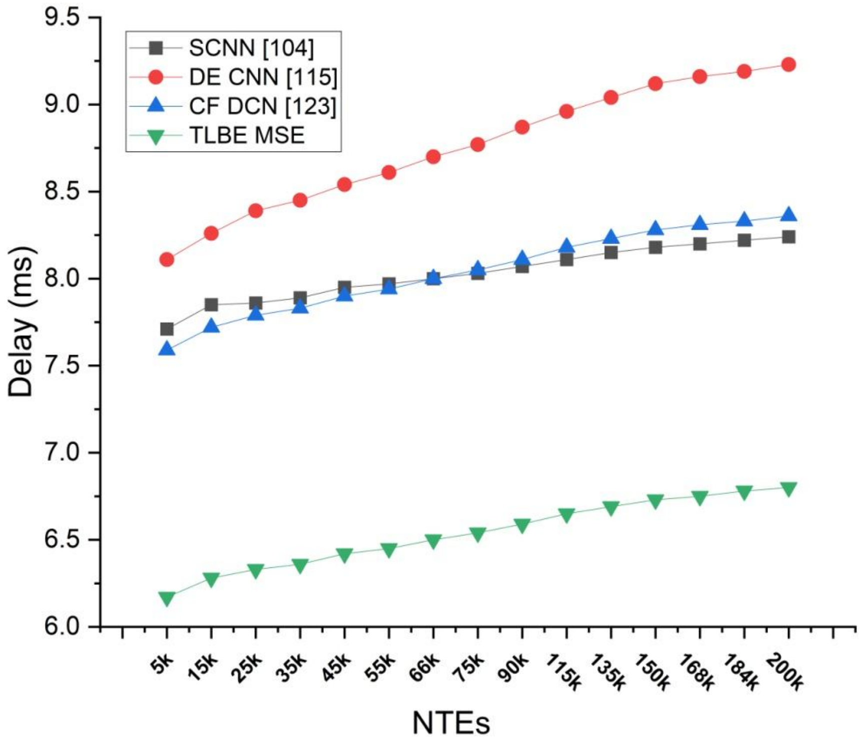

Figure 5.8 Delay needed for classification of different emotional disease types

As a result of this, the suggested model exhibits, in Fig. 5.8, 6.5% lower latency when compared to SCNN [100] 8.3% lower delay when compared to DE CNN [117], and 6.2% lower delay when compared to CF DCN [239] across various datasets. The proposed approach can be implemented for a broad range of real-time applications due to these improvements.

5.3.1 Conclusions

In interest to represent EEG signals as multidomain vectors, the suggested model makes use of a mix of DCT, DFT, DWT, MFCC, and iVector characteristics. These vectors may then be used for high-efficiency classification procedures. In addition to this, the model makes use of GWO-based feature selection, which contributes to the maximization of inter-class feature variance levels across a variety of class types. Cascaded neural networks can perform operations with minimal latency and high accuracy across a variety of emotional class types as a result of combining several distinct models. Many EEG datasets were used to test the model, and the outcomes were compared to a wide range of state-of-the-art analytical methods. The suggested model was shown to be 5.9% more accurate than SCNN [100] 3.5% more accurate than DE CNN [117] and 9.2% more accurate than CF DCN [239] based on this comparison. Furthermore, it was found that the model outperforms SCNN [100] DE CNN [117], and CF DCN [239] by 6.5%, 1.9%, and 5.9%, respectively. Further research revealed that the model could achieve 19.5% higher recall than SCNN [100]. This is made feasible by the use of several different Neural Network models, all of which work together to make the categorization process more consistent. The proposed model extracts a limited number of feature sets, which enables it to decrease the number of classification steps as well as the number of iterations that are required for the diagnosis of emotional disorders. As a consequence of this, the suggested model exhibits a latency that is 6.5% lower when compared with SCNN [100], 8.3% lower when compared with DE CNN [117], and 6.2% lower when compared to CF DCN [240] across a variety of datasets. As a result of these modifications, the model that has been provided is now capable of being used for a broad range of different real-time applications. In the future, it will be necessary to evaluate the suggested model using numerous datasets, and it will be possible to enhance it by integrating hybrid bio-inspired models. In addition, its performance may also be enhanced by integrating CNNs with Recurrent NNs, Q-Learning, Autoencoders, and other deep-learning techniques. This is done to optimize its performance in a context-sensitive manner in a variety of different circumstances.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

"Everything is theoretically impossible until it is done. "

-Robert A. Heinlein

6.1 CONCLUSION

The primary emphasis of this thesis has been the development of effective EEG classification approaches that could be used to identify mental disorders and stress early on. New methods have been introduced and implemented in interest to address the constraints and challenges that exist in the field following a thorough analysis of the EEG processing techniques currently in use. The newly established preprocessing approaches, sophisticated machine learning models, and interpretability methodologies have shown some promising outcomes in enhancing the accuracy and reliability of illness detection based on EEG datasets and samples.

Issues like artifact removal, noise reduction, and feature extraction have all been effectively handled by the preprocessing approaches that have been presented. The artifacts and noise in the EEG signals have been efficiently eliminated from the datasets and samples by using techniques such as ICA or adaptive filtering. As a result, the datasets and samples are now cleaner and more dependable. The EEG signals have been analyzed using the feature extraction approaches that have been used, such as time-domain analysis, frequency-domain analysis, and time-frequency analysis. This has resulted in the collection of significant information that has enabled the extraction of discriminative features that can be used for classification.

Classification accuracy is improved by combining advanced signal processing techniques like Wavelet, Hilbert, Fourier, and Cosine transforms, along with robust feature extraction and selection methods, as seen in the AMVAFEx model. This model uses variance-based feature selection to minimize redundancy and employs MFCC and iVector methods to capture relevant features. With high precision and recall, it's adaptable to diverse EEG applications. Additionally, a CNN-based model with transfer learning, using ResNet 101, Mobile V Net2, and YoLo, helps reduce variability among stress and emotional disorder classes. Ensemble classification, integrating classifiers like Naïve Bayes, SVM, Random Forest, Logistic Regression, and MLP, enhances accuracy by leveraging each classifier's strengths. Cross-validation further refines performance, producing outputs that indicate an individual's stress level, providing insight into their emotional state.

In comparison to other methods already in use, the newly created machine learning models have shown much better performance. Deep learning architectures, ensemble models, and transfer learning approaches have all been adapted specifically for EEG classification tasks and given optimal performance as a result. These models have shown that they can learn complicated patterns and extract relevant information from EEG data, which results in illness detection that is accurate and dependable. The clinical interpretability of the models was improved as a consequence of the interpretability approaches that were used in this study. These methods gave insights into the areas or patterns within the EEG signals that contributed the most to the classification findings.

6.2 FUTURE SCOPE

There are several potential routes for more study and development, although efficient categorization of EEG for the early identification of stress and emotional issues has advanced significantly thanks to thesis work. The following potential horizons have been identified:

Validation on bigger and more diversified datasets:

The suggested strategies and models need to be tested on larger and more diverse datasets that include a broad variety of emotional and stress-related diseases. This will guarantee that the suggested methods can be generalized to a variety of patient groups and therapeutic contexts and that they are resilient.

Integration of multimodal data:

Although EEG signals give useful information on their own, merging them with data from other modalities, such as fMRI, heart rate variability, or subjective measurements, may improve the accuracy and reliability of illness detection. To increase the overall performance of the classification models, future research should investigate the possibility of fusing various modalities into a single model.

Processing in real-time and online:

Processing EEG data in real-time and online is essential for clinical applications because it allows continuous monitoring and rapid intervention. Further study should concentrate on the development of effective algorithms and models that are capable of processing EEG data in real-time, which would make it possible for instant feedback and action.

Implementation and validation in the clinical context:

It is vital to collaborate with medical experts and clinical institutions in interest to verify the created methods and models in actual clinical settings in the real world. To further prove the practicability and efficacy of the suggested methods, clinical trials should be carried out, and evaluations of their usability, accuracy, and therapeutic relevance should be carried out.

Ethical issues and the preservation of personal privacy:

EEG data provide sensitive information about the brain activity of people; hence, ethical concerns and privacy protection measures should be carefully considered. In the future, research should concentrate on building rigorous frameworks and recommendations for the ethical treatment of EEG datasets and samples, as well as for the anonymization and safe storage of datasets & samples.

In conclusion, this thesis has made major advances in the area of efficient EEG categorization for the early diagnosis of emotional illnesses such as stress and anxiety. The newly established strategies and models have shown considerable improvements in terms of their accuracy, dependability, and interpretability. However, further research is required to verify and enhance these methods on bigger datasets, integrate multimodal data, allow real-time processing, undertake longitudinal studies, validate in clinical settings, and address ethical problems. Moreover, these methods must be validated in real-world contexts. The area of EEG-based illness identification has the potential to continue to progress, provided that these future goals are addressed. This would result in improved early diagnosis, tailored therapy, and improved management of stress and emotional disorders.

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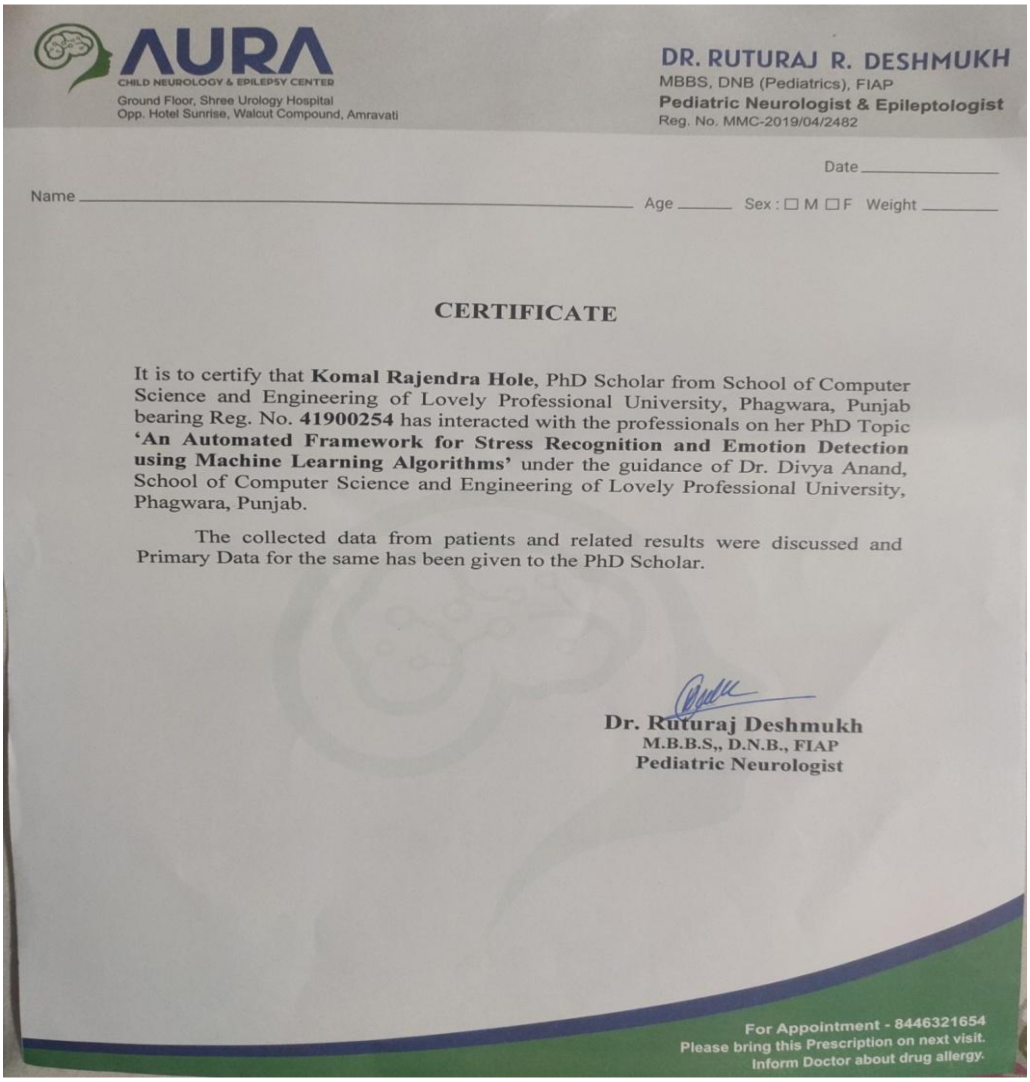
Annexure I

- Reference data set has been collected and authenticated by medical expert.



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Date ______

Name ______ Age ______ Sex : ☐ M ☐ F Weight ______

CERTIFICATE

It is to certify that **Komal Rajendra Hole**, PhD Scholar from School of Computer Science and Engineering of Lovely Professional University, Phagwara, Punjab bearing Reg. No. **41900254** has interacted with the professionals on her PhD Topic **'An Automated Framework for Stress Recognition and Emotion Detection using Machine Learning Algorithms'** under the guidance of Dr. Divya Anand, School of Computer Science and Engineering of Lovely Professional University, Phagwara, Punjab.

The collected data from patients and related results were discussed and Primary Data for the same has been given to the PhD Scholar.

Dr. Ruturaj Deshmukh
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Pediatric Neurologist

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Inform Doctor about drug allergy.