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NEURAL NETWORKS ALGORITHM FOR EMOTION RECOGNITION USING MINDWAVE MOBILE (EEG)

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Master's Thesis

Supervisor

Asst. Prof. Dr. Timur İNAN

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The thesis/dissertation titled “Neural Networks Algorithm for Emotion Recognition Using MindWave Mobile (EEG)” prepared by Mahdi Hamdi and submitted on 22/12/2023 has been **accepted unanimously** for the degree of Master of Science in Information Technologies.

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I hereby declare that all information data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

Mahdi Imad HAMDI

Signature

DEDICATION

I dedicate this seminal work to my first-class supervisor who taught me, supported me, and guided me through my research career and project creation. His guidance and advice were inspiring, his high scientific background was a source of strength for me and for this scientific project. Thank you, my teacher.

I also dedicate this work to my mother and father, who are the ones who brought me to this stage of excellence during the course of my life. Words and letters do not contain my gratitude to you, and your favor is never forgotten. You were my support throughout my academic career. May God keep you as an asset to me.

To my wife and my dear, you have always been a motivation and support for me. I do not forget your encouragement, patience, and endurance during this study and the distance that kept me away from you and my daughter, may God protect you.

to everyone who taught me a letter and provided me with information and was a positive source and motivation to complete my studies those include my sisters, friends, and loved ones, especially my cousin Haider and my friend Haitham.

ABSTRACT

NEURAL NETWORKS ALGORITHMS FOR EMOTION RECOGNITION USING MINDWAVE MOBILR(EEG)

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Emotion recognition using Mindware signals and neural networks is a challenging field due to the complexity of human emotions and the diversity of individual brainwaves. It can take a lot of experimentation and refinement to achieve accurate and reliable results. However, with the data, algorithms and technologies used it has many potential applications. Overall, it is an exciting and challenging field with many possibilities for further research and development. The choice of algorithm depends on the specific problem and the available data. Each algorithm has its own strengths and weaknesses. Choosing the right algorithm requires careful consideration of the data, features and parameters used. The general process includes collecting MindWave data from the MindWave device, pre-processing the data to remove noise and artifacts, extracting features that represent the user's emotional state, training the neural network using the labeled data, and testing the accuracy of the neural network on the new data.

Keywords: Emotion Classification, EEG Signals, Mindwave Mobile, Emotion Recognition, Deep Learning Methods, Neural Networks Algorithms for EEG.

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ABBREVIATIONS

AI	:	Artificial Intelligence
MWM	:	Mind Wave Mobile
BCI	:	Brain-Computer Interfaces
EEG	:	Electroencephalogram
HCI	:	Human-Computer Interfaces
PCA	:	Principal Component Analysis
LDA	:	Linear Discriminant Analysis
PCA	:	Principal Component Analysis
GPUs	:	Graphics Processing Units
LFDA	:	Local Fisher Discriminant Analysis
SVM	:	Support Vector Machine
RNN	:	Recurrent Neural Network
CNN	:	Convolutional Neural Network
GRU	:	Gated Recurrent Unit
LSTM	:	Long Short-Term Memory

1. INTRODUCTION

Artificial intelligence (AI) has become widely used in many fields, including medicine, industry, agriculture and many other fields that we may use in our daily live without realizing it. the development took place in the world of technology and the revolution of artificial intelligence has become a reality to apply what was a fantasy. Where it became possible to control the machine using the human brain through brain waves as if the machine is one of the parts of the human body. We know that any movement of the organs of the human body moves through orders coming from the brain, for example, if a person wants to move his hand, the first stage will be thinking about moving the hand, then the brain transmits the instruction through brain waves to the hand to move it and carry out certain tasks. Nowadays with the development of artificial intelligence, it has become possible to install prosthetic limbs for the disabled and move them in a manner similar to human limbs through devices that simulate the electrical activities of the brain.

Since the discovery of computers, there has been communication between humans and computers through programs or other peripherals. The process that provides interaction between users and computers is called “Brain-Computer Interfaces (BCI)”. Because of the use of hands-on Electroencephalogram (EEG) signals in a portable form, it has been favored in “BCI applications”. Where EEG technology measures the electrical activity of the brain, many applications benefiting from these activities have been developed in recent years. These applications have been used for several purposes, including medical, scientific, entertainment, psychological, and neurological treatment, and other applications [1].

Synthetic stimuli are directly associated with the activities of the human brain via a “Brain-Computer Interface (BCI)”. Through this, an interactive path is provided between the human brain and external devices for different types of applications. This interaction process begins with a recording of brain activities by taking incoming signals and analyzing and processing them to discover the intention of the user. BCI systems and applications have been an ongoing topic of research for decades. The most attractive research is dealing with the description and identification of feelings by using physiological and non-physiological cues to distinguish emotions. Figurative facial expressions, vocal signals, and body gestures are non-physiological signals, while physiological signals are signals that are detected by wearable devices, as they are invisible or audible. such as EEG devices [2].

Electroencephalogram (EEG) devices can be defined as devices that record the state of electrical activities that occur in the brain during the exercise of physical and chemical brain activities. The brain produces signals that have various values of frequencies and amplitudes according to the human condition, whether he is awake, asleep, or in a mood state. As it is considered aperiodic signals, “brain waves are divided into five frequency bands of EEG signals: Theta, Alpha, Delta, Beta, and Gamma” each of which is sandwiched between certain values of frequencies measured in Hertz [1].

Others have defined it as a tool that records and measures the electrical potential of brain waves. It works on the processing of vital signs in the applications of the biomedical field.

“Electroencephalogram (EEG) signals” are an essential source in practical studies and assessment of human brain activity. Several research areas related to biomedical EEG signals have been developed.

The “EEG electrodes” are placed directly on the scalp without penetrating it. It becomes easier for researchers to obtain results from EEG signals as the number of electrodes used is increased. Single EEG signals were used to measure brain waves. The application of cognitive activity is one of the methods of brain stimulation that produces brain waves that are found specifically in the field of active thinking [3].

Frequency meters are quiet expensive devices that were used in hospitals in the recent years. Some devices that can read thought waves have been manufactured at user-friendly prices, such as the NeuroSky Mind Wave Mobile (MWM). The availability of these EEG devices has helped in opening new doors for developers in the field of technology to come up with new ideas that help and meet all needs. where it’s first started with computer games in order to reach real interaction between the user and the games and evaluate the player's feelings to create more interaction and fun [4] [5]. There are many wonderful ideas in which the electroencephalogram is used, such as the safe driving of cars, depending on the engineering environment and the ability of the driver to make the appropriate decision and stop the car immediately [6].

One of the important research issues in human-computer interfaces (HCI) and EEG fields is emotion recognition. Classifying emotions into a certain number of categories can be considered the primary goal of emotion identification.

These applications focus on feelings and emotions, and all of this happens from brain signals read by EEG machines [7][8].

1.1 MOTIVATION

The main objective of this project is to identify the user's feelings and to know and classify the person's psychological state. This technology can be used to solve security issues or help treat patients with psychological and neurological conditions. Also, through this project, it is possible to benefit from the application of several other projects that contribute to meeting the needs of users, for example, helping people with motor disabilities who have lost one of their limbs and whose minds are still intact. Their minds can be used to meet their needs by sending the waves emitted from the brain using EEG to process them and send them to the machine using several tools (Bluetooth, Arduino, or other tools) so that the machine can be controlled to implement a specific command and meet the user's needs.
It was based on several research sources and papers that researchers worked on in the field of reading brain waves to classify the psychological state. By wearing a device with electrodes placed on the scalp and using brain stimuli by applying cognitive activity.

1.2 PROBLEM STATEMENT

Dealing with datasets is often expensive because there are a large number of dimensions or features that reflect categories of sentiment. These properties are reduced by using LDA and PCA feature selection techniques. The feature choices are also not strong enough if there are a variety of features and there are close to 100 features. Furthermore, using supervised machine learning methods, the emotion recognition dataset is classified into the EEG data. Because supervised machine learning methods take so long to recognize emotions, they are expensive.

1.3 CONTRIBUTION

In the beginning, feelings were described by recognizing facial gestures by classifying images, or through audio analytics. Now, by using electrical brain waves, these traditional methods have been dispensed with, and thus it has become easy to describe a person's feelings through this technique. There are other uses through which it is controlled without the need to use analytical and control devices.
This project relied mainly on:

a. Analyzing brain waves to describe the user's feelings.

b. Using stimuli to activate and stimulate the brain.
c. Interpret the results by analyzing brain signals.
d. Knowing the final state of the person (joy, sadness, fear).

1.4 AIM AND OBJECTIVE

An integrated system was built to read and interpret the psychological state of the user through brain waves.
Reading the electrical waves of the brain through the (Mind Wave Mobile) device.
This application receives, analyzes and interprets the data received from the MWM device in real-time and displays the final results in emotion recognition. This system can be used in the medical, psychological and security fields.

2. LITERATURE REVIEW

This chapter discusses EEG signals, relevant context information, how to select features, and classification methods. Critical analyses were also conducted to find a gap in the recent research.

Electroencephalography (EEG) is an important area of research involving neuroscience, medical engineering, and neuro-engineering “e.g., Brain-Computer Interfaces (BCI)” [9]. Evidenced by the high temporal resolution, non-invasive nature, and fairly low financial cost, the high importance of the EEG prompted researchers to exploit EEG signals in functional applications such as sleep analysis [10] and detection of seizures [11] [12]. The conventional EEG classification line consists of two stages: artifact removal and feature extraction. The base level “EEG dataset” consists of a binary matrix (channel, time) of real values that reflect brain-generated potentials that need to be recorded by scalp-mounted peripherals in conjunction with specific task conditions [13]. “Because of their advantages, EEG data are suitable for machine learning”. Thought waves have been subjected to “a large number of machine learning and modularity recognition algorithms, for example, principal component analysis (PCA) and discriminant analysis (LFDA) are frequently used to reduce feature dimensionality, supervised machine learning methods such as Support Vector Machine (SVM), linear feature analysis (LDA) and decision trees are frequently used” [14] [15] [16]. On the other hand, neural network models did not get attention at the same level as other classification algorithms. “This is due to the fact that neural network requires high computational power”. However, recently it has been used due to the availability of high-performance computational equipment, such as graphics processing units (GPUs), which have provided researchers in the field of neural networks with five affordable and effective solutions to hardware problems. The availability of analytical developments has greatly enhanced the efficiency of research not only in other disciplines but also in the analysis of the EEG data. However, the EEG classification deep learning tasks were categorized into six categories: kinematic imagery, mental workload, emotion recognition, seizure identification, sleep phase recording, and potential event-related detection [12].

Emotions can be defined in psychology as one of the states of a belief that lead to psychological changes and in turn, reflect the individual's thoughts and behaviour on the physical changes in that state [17] [18]. Affective neuroscience is interested in delving into the neural networks that support emotional processes and their implications for cognition, physiology and behaviour [19]. The concept of emotion plays a social, adaptive or motivational role in human life due to the unique characteristics of human behaviour [20]. Emotions have an effective role in decision-making, perception, human interactions, and thought. Emotions are represented in two basic forms: positive and negative representations, each of which has factors affecting human health and job performance [21].

Through two perspectives, the feelings that are felt in general can be understood The first is the categorical perspective, which enables us to learn about the basic emotions encoded in our evolutionary biology. The wheel model describes the basic sentiments in Figure 2.1

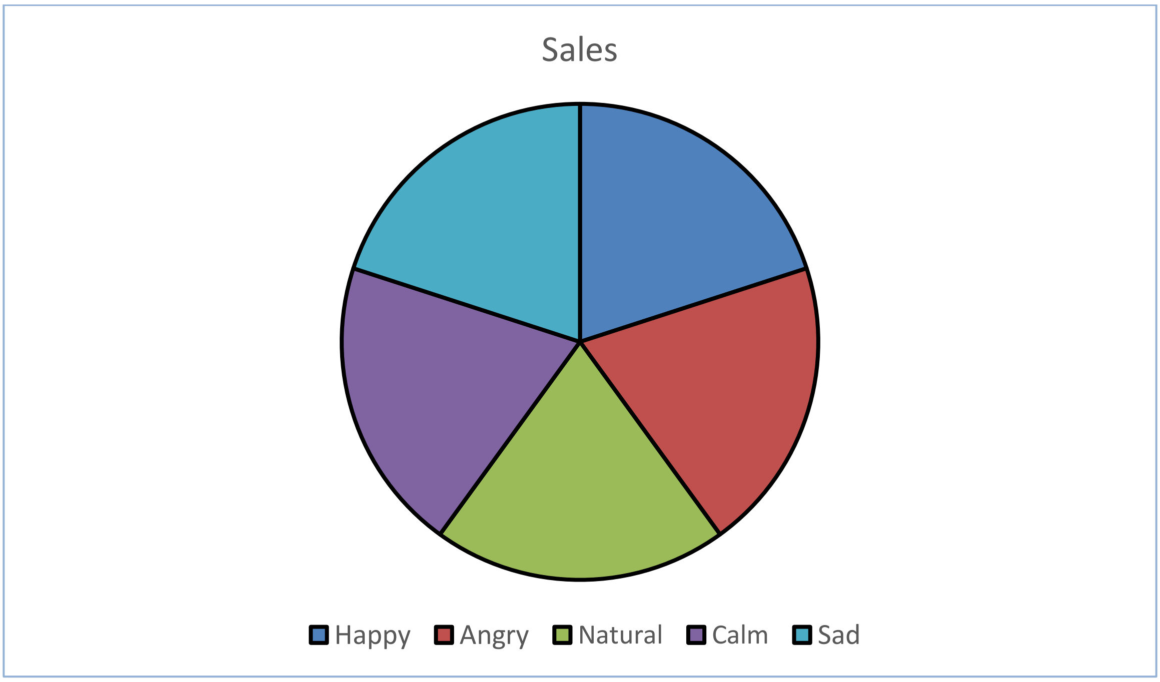

Figure 2.1: Eight Basic Emotions.

The second is a dimensional perspective. Emotions are categorized according to arousal, control, and valence. Valence is calculated in terms of "positive and negative emotions". Although arousal and superiority are quantifiable on a scale from highest to lowest [23].

Emotions are detected by having people watch videos that have been pre-formatted with different emotions by experts. During the viewing of the videos, the "evaluation of the EEG signals is usually followed by the subjective evaluation of emotion". The subjective evaluation and original classes of emotions are then translated into a pair of valence arousal values, which are widely used in describing emotions [24]. By collecting the brain wave signal, machine learning is adopted, developed, and optimized for emotion classification studies.

Mindwave headset is considered one of the best methods for recording electroencephalography. It can also be defined as an electrical device through which the electrical waves of the human brain are measured by placing electrodes on the scalp and frontal area. Inverting or multiplying the signals and amplifying them [25].

Collecting brain signals requires looking at the EEG for emotion classification, the electrode positions of the EEG signals, the electroencephalogram (EEG) signals and their frequency ranges:

As a physiological indicator, EEG is essential to synthesize the electrical activities of neurons in the human cerebral cortex. The EEG has the most detailed features for emotion classification, such as frequency spectral bands. In the human brain, especially the limbic system, as shown in Figure 2.2 below, there are three main mechanisms whereby emotion and memory are strongly active in the brain: the hippocampus, the amygdala, and the hypothalamus. The hypothalamus is responsible for emotional responses, while the amygdala is responsible for processing emotional information based on situation recognition and threat analysis.

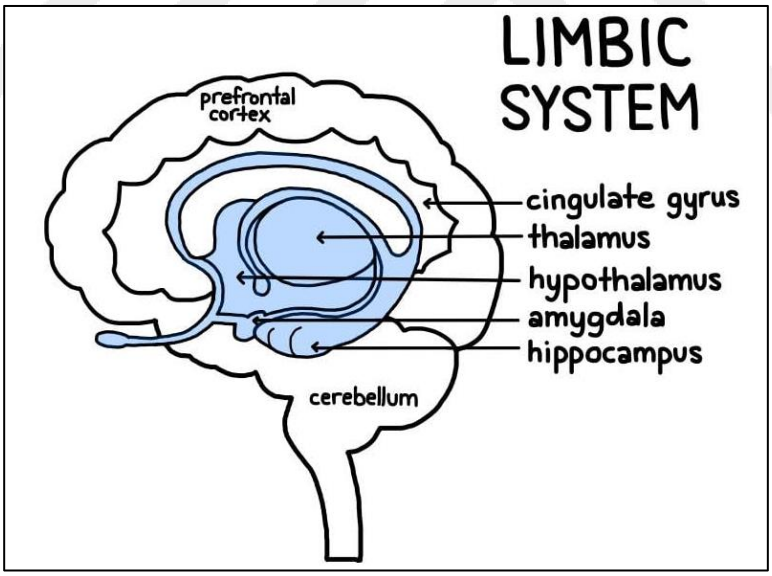

Figure 2.2: The Limbic System [26].

the electrode position of the EEG facilitates the repetition and recording of the EEG reading. The protocol for pericrania implantation of these electrodes usually complies with the standards of 10-20 international systems. “10” and “20” denote the true distance between electrodes next to each other, which is 10% or 20% of the total right-to-left or front-to-back distance of the skull, respectively. Figure 2.3 shows a typical electrode location according to the SI 10-20 positioning.

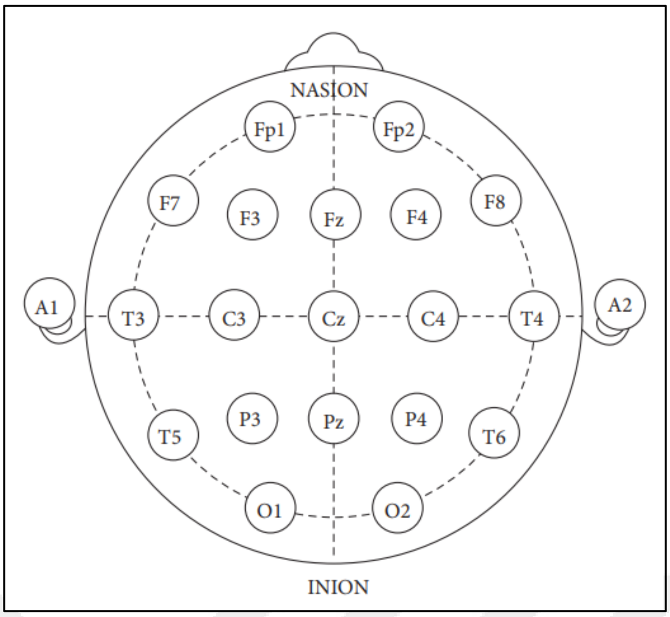

Figure 2.3: The 10-20 EEG Electrode Positions [12].

EEG signals, which is a frequency band divided into five different signals (or band) "i.e., Alpha, Beta, Gamma, Theta, and Delta", as listed in Table 2.1. Channel location and sampling rate vary according to EEG units, which typically contain "between 16 and 32 channels on a single headset" [27]. As in Table 2.2.

Table 2.1: Electroencephalogram (EEG) Signals and Their Frequency Bands.

Band name	Frequency band (Hz)	Functions
Delta	<=4	It is typically liked with and the subconscious mind occurs during deep sleep.
Theta	4-7	Sleeping and dreaming both occur. They are typically associated with the subconscious mind.
Alpha	8-15	Generally correlated with a relaxed yet conscious mental state and associated with brain stimulation.
Beta	16-31	Typically correlated with the state of the conscious mind and happens during intensive mental activity based.
Gamma	>32	Typically related to extreme activation in the brain.

Table 2.2: EEG Headset.

Band name	Frequency band (Hz)	Functions
Delta	<=4	It is typically associated with and the subconscious mind occurs during deep sleep.
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For emotion recognition, computational methods have been successfully applied in the task of correlating emotional changes with EEG signals [28][29]. Emotional changes can be detected and further classified from the signals coming from the EEG if appropriate stimuli of the emotions are applied. Because of the characteristics of signal and noise, automatic emotion recognition is usually limited to a small number of emotion categories, which leads to subject-dependent problems. This is what made researchers discuss subject dependence by proposing trait-based emotion recognition models.

Previous researches and research papers have looked at five common ways to improve mind wave reading performance and users' emotional experiences: music, photos, videos, virtual reality, and music videos. For the purpose of stimulating and identifying the emotion, the datasets are listed.

The most widely used dataset is a deep dataset, which can be freely accessed by researchers to conduct research.

The researchers introduced a supervised machine-learning method for emotion classification. A rating algorithm is used to analyze the relationships between consumers' instrumental ratings and measures of mood in the sense of past observations using EEG data.

Then by examining the physiological associations between feelings and personality on a linear and non-linear scale [30].

Others have proposed an approach to use a dynamic blueprint to model the multichannel EEG features needed for EEG emotion classification. The proposed graph explores the intrinsic relationships between different neurophysiological channels by training the neural network on an adjacent matrix. In addition, the adjacency matrix is used to learn additional discriminatory features for the purpose of enhancing emotion recognition in the EEG [31].

A neural network model has been proposed inspired by the specialty of neuroscience, which takes into account the asymmetry of the cerebral hemispheres (left and right hemispheres) in terms of emotional response. The asymmetry of the two hemispheres decreased the possibility of field differences between the source and the target domains in each hemisphere, which enhanced emotion recognition when an adversarial neural network was used as a classifier [32].

In previous studies, various approaches have been employed to address the task of emotion classification using EEG signals. These approaches investigate the relationship between brain activity and emotional responses, utilizing different sensory stimuli such as visual and auditory cues like words, images, and video clips to influence an individual's emotional state. For instance, Tomarken et al. hypothesized that resting forehead asymmetry can predict emotional affect and conducted research using electroencephalography (EEG) to explore this relationship [33]. Similar findings were reported by Davidson et al., who indicated that brain electrical activity is associated with emotional responses [34].

Numerous studies have utilized EEG signals to classify and examine emotions. Lee et al. focused on communication patterns dependent on EEG signals for classification [35]. Wang et al. conducted an experiment to record emotional states through EEG signals while participants were exposed to emotionally stimulating films. Dwarves utilized self-assessment in their research (SAM) and created a dataset of six volunteers to investigate emotion state classification based on EEG signals, employing SVM for accuracy calculation [36]. Murgaban et al. employed the discrete wavelet transform to analyze EEG signals and highlighted the challenges researchers face in collecting EEG data using clinical EEG devices [37]. Penning et al. added that while clinical devices offer high accuracy, they pose challenges for participants and patients [38]. Clinical data collection restricts movement, and electrodes placed on the scalp may leave residue on the hair. Moreover, the high cost of medical devices has led to the development of commercial alternatives to address these issues.

The emergence of deep learning techniques has garnered attention in the field of emotion recognition based on brain waves. “Convolutional Neural Networks (CNNs)” have been widely utilized in EEG-based emotion classification tasks due to their ability to automatically learn spatial and temporal patterns in data. Wang et al. proposed a deep CNN architecture for emotion recognition from EEG signals, outperforming conventional machine learning techniques [39]. In another study, Li et al. introduced a hybrid CNN architecture “combined with bidirectional Long Short-Term Memory (BiLSTM) to improve accuracy on a benchmark dataset” [40].

“Recurrent Neural Networks (RNNs)”, including variants like LSTM and GRU, are suitable for modelling sequential dependencies in time-series data like EEG signals. Researchers have employed RNN architectures for emotion classification. Zheng et al. introduced a multi-channel LSTM network for emotion recognition from EEG, demonstrating competitive accuracy and robustness to artifacts [41]. Li et al. proposed a hybrid LSTM-CNN architecture that effectively captured both temporal and spatial features in EEG signals, resulting in improved emotion classification performance [42].

Deep Belief Networks (DBNs) have also been utilized in emotion classification tasks to learn hierarchical representations of EEG data. DBNs consist of stacked Restricted Boltzmann Machines (RBMs) that progressively learn more abstract features. Yao et al. utilized a DBN-based approach for emotion recognition from EEG signals, achieving notable performance across various datasets[43].

Ensemble methods, which combine multiple classifiers, have been explored for EEG-based emotion classification. Chen et al. proposed an ensemble framework that integrated multiple CNN and LSTM models, leveraging the complementary strengths of each model to enhance accuracy on emotion classification tasks [44].

These approaches and architectures highlight the ongoing efforts in the field of emotion classification using EEG signals, aiming to improve accuracy and robustness in capturing and understanding human emotions.

In this study, algorithms and classification methods were highlighted and compared in terms of accuracy and loss. Where the model was trained using LSTM alone, then using GRU alone, and finally integrating the GRU with CNN, on a dataset that was specially configured in this study using the MINDWAVE device and processing it. After training, the initial results for both LSTM and GRU showed an accuracy rate ranging between 65% to 73%, while the final results showed preference using the hybrid algorithm between GRU and CNN, where the results had an accuracy of 80% to 84%. Note that the accuracy could be much higher if ready-made datasets were used, because the used dataset contains fewer shapes and the reason of that is the use of commercial intellectual wave devices contains fewer sensors, which limits the possibility of capturing more shapes and signals, unlike EEG medical devices.

3. METHODOLOGY

3.1 INTRODUCTION

Emotion is the basic description through which a person expresses his feelings, which affect a person's natural activities and decisions in his daily life. One of the techniques of artificial intelligence in the modern era and the development of applications of “artificial intelligence”, is the recognition of human emotions and interaction between humans and computers. The unit of emotion control, the brain is the primary organ responsible for information processing and management within the human body. It generates physiological signals that are captured and analysed through electroencephalography (EEG). Emotions are closely linked with the behaviour of the flute in most cases, and the actual thoughts of people can reflect on human feelings, emotional states and psychological conditions [45]. Decision-making in daily life and physiological activities can’t be separated with emotions [46]. Therefore, EEG signals have the capability to provide insights into an individual's current emotional state in real-time. There are many methods for detecting emotions, identifying them, and extracting features and one of the most important of these methods is the use of EEG signals [47]. In the twentieth century, feelings were divided into emotions closely related to human physiological responses to psychologists Pail Ekmean. Therefore, by classifying brain wave emotions, we can obtain categories of feelings [48].

This chapter presents the algorithms and methods used in this study to classify emotions from EEG signals. The chapter begins with an explanation of the EEG data that can be accessed by electroencephalogram readers and that were used to test the model created for emotion recognition. While the next section of the chapter provides a comprehensive summary of the methods for extracting and selecting features based on an optimization algorithm inspired by dynamics. Finally, the chapter shows how emotion classification of EEG waves was performed using a deep neural network that was fed well-selected features. The following figure shows the flow of the methodology that was built to classify feelings.

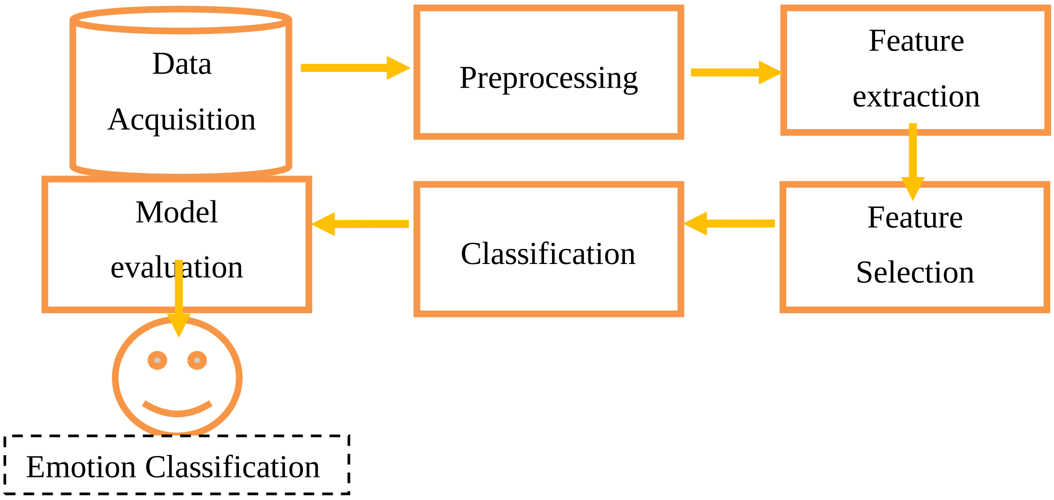

Figure 3.1: General Steps for Emotion Recognition.

In general, any EEG-based emotion classification model goes through several stages. This flowchart is an overview of the classification process and that the steps and methods can differ depending on the research question and its methodology.

3.2 OVERVIEW OF THE STEPS AND METHODS FOR THE FLOWCHART

a. Data acquisition: EEG signals are recorded while participants experience emotional stimuli, such as pictures, videos, or other motivational techniques.
b. Pre-processing: EEG signal lines are pre-processed to remove noise, artifacts, and underlying drifts. This can include filtering, artifact removal techniques, and feature extraction.
c. Feature extraction: Features are extracted from the pre-processed EEG signals. These features can be time domain, frequency domain, or time-frequency domain features. Examples are power spectral density, entropy, and capacitance.
d. Feature Selection: A subset of the most useful features is selected for classification. This can be done using various methods such as correlation analysis, mutual information, or principal components analysis.
e. Classification: The specified features are used as inputs to a classification algorithm such as a neural network. The algorithm learns to associate features with different emotional states such as happy, angry, sad, calm, or natural.
f. Model Evaluation: The performance of the classification model is evaluated using various measures such as accuracy, sensitivity, and specificity. The model can also be validated using cross-validation data or retained test data.

g. Emotion prediction: The final step is to use the trained model to predict the emotional state of the new EEG signals from the unseen participants.

3.3 STAGES OF DEVELOPING THE MODEL USED

3.3.1 The Preparation Stage

personal computer: Lenovo laptop with Intel core i7 8th Gen processor, 8GB RAM, running Windows 10 64-bit operating system with PyCharm and Python version(3.7) software installed.
MindWave Mobile Device: NeuroSky (MindWave Mobile2), a device that measures and reads electroencephalography, which is an important and essential part of this project. It works by capturing electroencephalographic signals from the human brain. It is considered a relatively low-cost device with the price, ranging between $100-500. The device consists of a headset, ear pad sensors in the form of an arm, and a clip placed on the forehead where the use of the clip is to ground the EEG electrode. The following figure shows the structure of the MindWave device used [49].

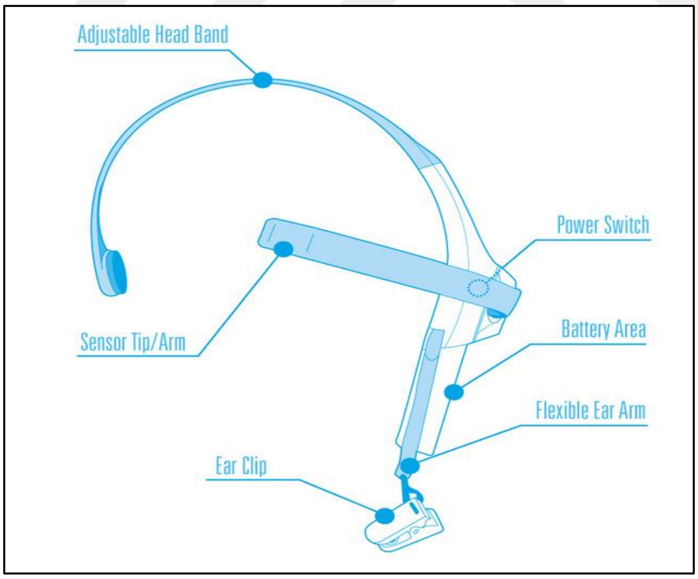

Figure 3.2: Mind Wave Mobile Device [49].

3.3.2 Some of the Features of the MindWave Mobile Device

a. Automatic wireless pairing, BT/BLE dual mode module (10 meters range), Static Headset ID (Headsets have a unique ID for pairing purpose).

b. Single AAA Battery, 8-hours battery run time.
c. Uses the TGM1 module.
d. Supported platforms: Windows, Mac, IOS, Android.
e. Weight: 90g.

Measures of MWM:

The MWM device uses a Bluetooth (BT) connection to connect with other devices such as a computer, mobile phone, or any other device that would like to be connected to MWM. The devices must be paired using BT according to the user manual from NEUROSKY [49]. The coupling of BT to MWM is as follows:

a. Raw Brainwaves
b. EEG Processing and output power spectrums (Alpha, Beta, etc.).
c. ECG signal. quality analysis, used. to detect poor contact and whether the device is off the head.
d. NeuroSky Extracting and processing the sense Scale of Meditation and Attention.

3.3.3 Data Collection Stage

This model was trained on five types of data extracted by the brain electric waves device for three different people at different times, their age ranged between 20-30 years old, with an average age of 26 years. Using the supervised technique MindWave Mobile device was installed on the scalp to collect EEG data for each person. A number of video clips were played that have different effects on feelings. The data for each case was collected while watching these clips. Then labeling this dataset according to the psychological state of that person while watching the video clip, whether the condition was (happiness, anger, calmness, sadness, and the neutral state).Things may get mixed up in some cases in which anger and sadness are exposed and may cause a problem in certain cases in provocative processes such as a person losing challenge and stimulating the anger process by annoying them through speech for the purpose of collecting data during the state of anger and distinguishing it from the state of sadness. This goes through stages of preparation and data processing. MindWave device wase first turn on to see it works fine. Then the Mindwave library was installed in Python, this library can be found on Neurosky's official website or through GitHub website. To connect the MindWave headset to the computer via USB or Bluetooth, a special function needs to be called from the library to initiate the connection.

After successful connection processes, EEG can be accessed by steps specified on the operating system and the programming language. Once This is done the process of reading data can be started. This data includes raw EEG data, attention levels, meditation and other metrics depending on the needs of the application.

3.3.4 Data Label

During the data collection process through the Mindwave device, the EEG data were labelled with the corresponding feelings during the reading process by means of the supervised technique. Separately, naming matrices were created for the divided data for each of the states (happy, sad, calm, angry, and neutral).

3.3.5 Data Preparation

Preparing segmented EEG data and corresponding labels for input into the neural network. These include reshaping the data into a 2D or 3D matrix, normalizing the data, and dividing the data into training and test sets. Through machine learning libraries or SKlearn library in the implementation of this pre-processing.

3.3.6 Loading the Data

After importing the necessary libraries, the data was loaded from five CSV files collected before. This contains EEG data recorded during different emotional states (happy, sad, angry, neutral, and surprised). This data then concatenated them into a single dataframe called all_data.

```
import pandas as pd
# Load the data
happy_data = pd.read_csv('Happy.csv')
sad_data = pd.read_csv('Sad.csv')
angry_data = pd.read_csv('Clam.csv')
neutral_data = pd.read_csv('Neutral.csv')
surprised_data = pd.read_csv('angry.csv')
# Combine the data
all_data = pd.concat([happy_data, sad_data, angry_data, neutral_data, surprised_data])
all_data = all_data.sample(frac=1).reset_index(drop=True) # shuffle the data
all_data = pd.DataFrame(all_data) # convert the shuffled data to a dataframe
```

Figure 3.3: Combine the Data into a Single Dataframe.

Here's a breakdown of the code:

happy_data = pd.read_csv('Happy.csv') - loads the data from the "Happy.csv" file into a pandas dataframe called happy_data.

sad_data = pd.read_csv('Sad.csv') - loads the data from the "Sad.csv" file into a pandas dataframe called sad_data.

angry_data = pd.read_csv('Clam.csv') - loads the data from the "Clam.csv" file into a pandas dataframe called angry_data.

neutral_data = pd.read_csv('Neutral.csv') - loads the data from the "Neutral.csv" file into a pandas dataframe called neutral_data.

surprised_data = pd.read_csv('angry.csv') - loads the data from the "angry.csv" file into a pandas dataframe called surprised_data.

all_data = pd.concat([happy_data, sad_data, angry_data, neutral_data, surprised_data]) - concatenates the five dataframes into a single dataframe called all_data.

all_data = all_data.sample(frac=1).reset_index(drop=True) - shuffles the rows in all_data randomly to ensure that the data is not biased towards any particular emotional state. The frac=1 argument specifies that the entire dataframe should be sampled (i.e. none of the rows are dropped), and the reset_index(drop=True) argument resets the index after shuffling the rows so that the index starts at 0 and increments by 1 for each row.

all_data = pd.DataFrame(all_data) - converts the shuffled all_data dataframe back into a pandas dataframe, in case any changes were made to the dataframe during shuffling. This line may not be strictly necessary, since all_data is already a pandas dataframe, but it ensures that the final output is a dataframe.

3.3.7 Pre-Processing After Loading the Data

To removes any rows in the all_data dataframe that contain missing (NaN) values. The inplace=True argument means that the original all_data dataframe is modified in place, rather than returning a new modified dataframe.

```
all_data.dropna(inplace=True)
```

Also to remove any unnecessary columns, such as the timestamp or channel names. Like removes the first column of the all_data dataframe, which contains the timestamp, as well as any other unnecessary columns. The iloc method selects rows and columns of the dataframe by integer index, and the [:, 1:] notation selects all rows (denoted by the :) and all columns starting from the second column (denoted by 1:).

```
all_data = all_data.iloc[:, 1:]
```

To create separate dataframes for each emotion category by filtering the all_data dataframe using the loc method and the Emotion column. Each new dataframe contains only the rows where the Emotion column matches the category (e.g., "Happy", "Angry", etc.).
Also to create "sample" dataframes for each emotion category by selecting a single row from each category dataframe. The row selected is arbitrary (e.g., happ.index[4] selects the 5th row of the "Happy" dataframe), and the columns selected are all columns between "Raw" and "mid-gamma". These sample dataframes are used for plotting or visualization purposes. As this code shows:

```
happ = all_data.loc[all_data["Emotion"] == "Happy"]

sample_happ = happ.loc[happ.index[4], 'Raw' : 'mid-gamma']
```

The distribution of feelings within a data frame after performing the prior operations on it before the input process. The following figure shows the emotion distribution process.

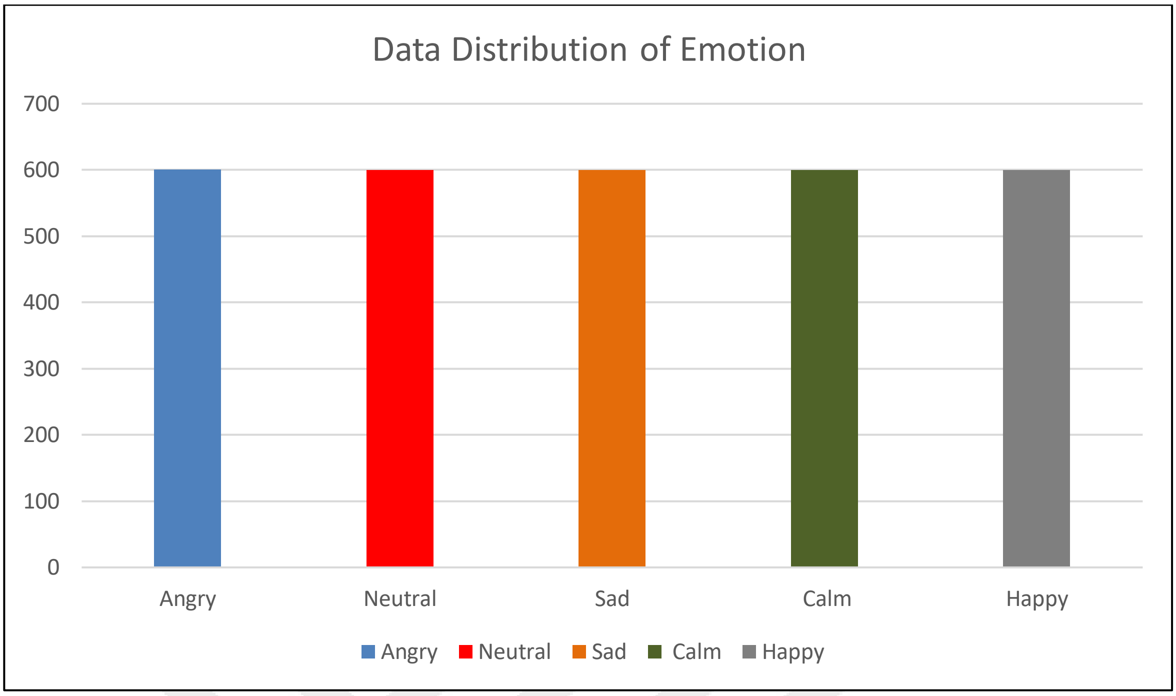

Figure 3.4: Emotion Distribution Process.

It has been noticed that the data frame for each category has the same size as the matrix, which consists of 600 elements distributed evenly among the sentiment categories. Some lines of code have been implemented to clarify the difference in the waveform chart for each category of feelings and the values that each type carries. For example, the graph of happiness columns that contain lines of brain wave data starts to increase to reach the highest value of 6,000 and then gradually decreases.

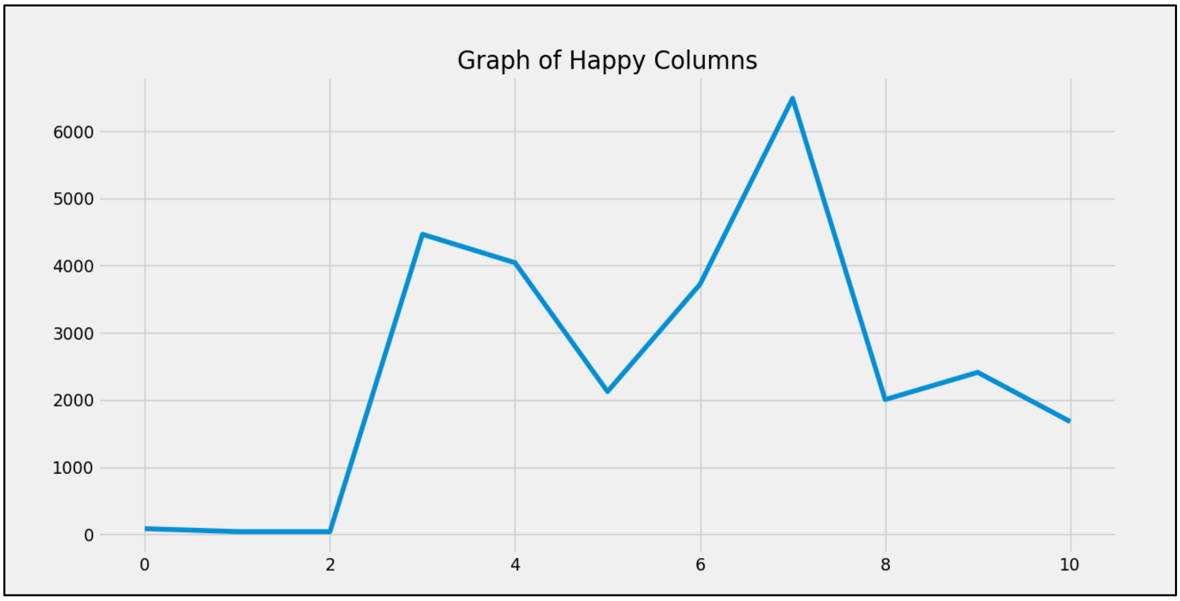

Figure 3.5: Line Chart of Happy Columns.

While the graph of the sadness columns increases to reach the highest value of 12,000 between 2-10 horizontally, as shown in the figure below:

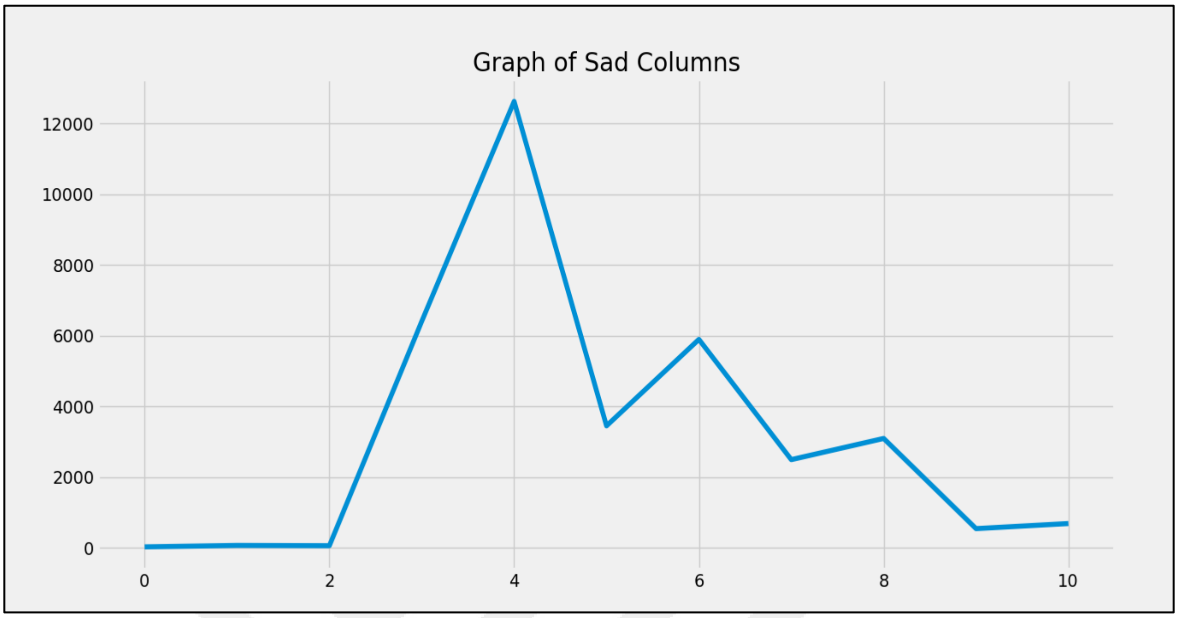

Figure 3.6: Line Chart of Sad Columns.

It has been noticed there is a big difference that describes the frame of each type of feelings and the scales reached by the values during the reading of the electroencephalogram. As shown in figure 3.6 of the anger framework, the highest value and its link is 7,000, and it begins to decrease gradually more than it is in each of the columns of happiness and sadness

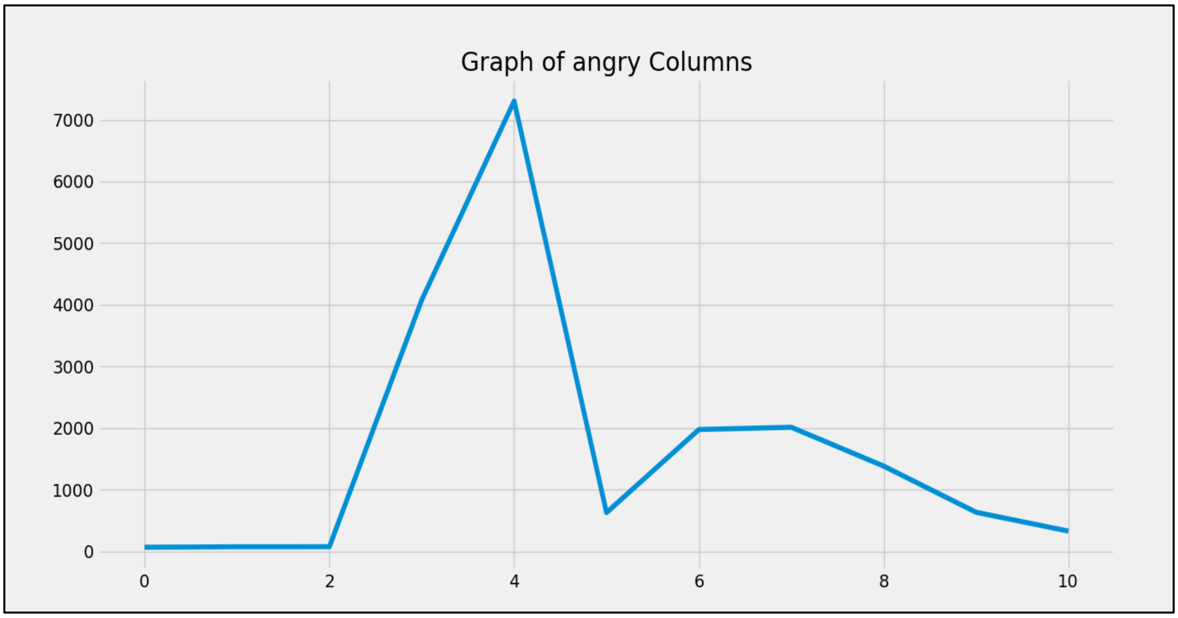

Figure 3.7: Line Chart of Angry Columns.

3.3.8 Data Preprocessing

a function has been defined called Transform_data that takes in a dataframe called all_data as input. Here is what the function does:

a. It creates a dictionary called encoding_data to map emotion labels to numerical values.
b. It replaces the emotion labels in the all_data dataframe with their corresponding numerical values using the replace method.
c. It separates the brain signals into a variable called x and the emotion labels into a variable called y.
d. It standardizes the x variable using the StandardScaler method.
e. It one-hot encodes the y variable using the to_categorical method from Keras utils.
f. It returns the standardized x and one-hot encoded y as output.

After defining the Transform_data function, the code calls the function on the all_data dataframe and assigns the output to X and Y. Then, it splits the dataset into training and testing sets using the train_test_split method from sklearn.model_selection. Finally, it prints out the number of features in the training dataset (which is the number of columns in the x_train variable).

3.3.9 Creating the Model

The model architecture consists of an input layer that takes a tensor of shape (batch_size, x_train.shape[1]) where x_train.shape[1] is the number of features in the input data.

The input is then passed through a GRU layer with 256 units and return_sequences=True parameter, which means that the layer will return output for each input time step, rather than just the last time step. The GRU layer also has a kernel_regularizer parameter that applies L2 regularization with a penalty of 0.001 to the kernel weights.

The output of the GRU layer is flattened into a one-dimensional vector using a Flatten layer, and then passed to a Dense output layer with 5 units and sigmoid activation function. The model is then compiled with the adam optimizer, mean squared error loss function, and accuracy metric.

Finally, the function returns the compiled model object, which is then used to train and evaluate the model on the training and testing datasets. The model's training history is also stored in a variable called history.

Architectures used in this study:

This study relied on EEG data for emotion recognition. Experiments were carried out on several types of artificial neural network architectures "LSTM (long term memory network), GRU (Gates Recurrent Unit), SVM (Support Vector Machines) and Convolution Neural Networks".

Support Vector Machines (SVM):

SVM is a popular machine learning model used for regression analysis and statistical classification. It is a binary model and a linear classifier, assuming that the classifier objects are linearly separable. SVM defines the most prominent margin in the feature space and utilizes interval maximization as a learning strategy. Kairui Guo employed "Fuzzy Cognitive Mapping (FCM) and SVM" in their research for emotion recognition, incorporating both facial expressions and EEG signals. They conducted experiments on a comprehensive dataset and performed a deep analysis of the data [50]. To reduce noise, the researchers divided the data into short time periods and applied data compression techniques to minimize spacing between the data. They utilized the wavelet transform method for feature extraction, which was then used in the classification process. Thejaswini conducted an empirical comparison using SVM between a deep dataset and a SEED dataset, achieving good accuracy in both cases [51].

SVM has its advantages and disadvantages. One of its advantages is its ability to effectively reflect the brain's state. By employing signal processing techniques in the frequency and time domains, it can analyse static signals and leverage the benefits of irregular movement. It offers high computational efficiency and allows for the extraction of relevant information from the data. However, it may not perform well with unstable signals, and its computational complexity can be a drawback due to the large number of arithmetic operations [52-54].

The mathematical formulation of SVM involves finding an optimal hyperplane that maximizes the margin between the two closest data points from different classes in a training dataset. These data points, known as "support vectors," lie on the boundary of the decision regions.

Solve the optimization problem by the following mathematical formula:

minimize:

$$\left(\frac{1}{2}\right) * \left||w|\right|^2 + C * \Sigma\xi_i \tag{3.1}$$

subject to:

$$Y_i * (w^T * X_i + b) \geq 1 - \xi_i, for\ all\ i = 1\ to\ N \tag{3.2}$$
$$\xi_i \geq 0, for\ all\ i = 1\ to\ N$$

Support Vector Machines (SVM) can also be applied to classify emotions using EEG data. Here's a mathematical explanation of SVM for emotion classification:

Data Representation: The data of EEG is typically displayed as an Array X, where each column denotes a feature and each row a sample (e.g., power spectral density, frequency bands, etc.). The corresponding emotion labels are represented as a vector Y.

The formulation for Binary Classification: SVM can be used for binary emotion classification by assigning labels of +1 and -1 to the two emotions of interest. The objective is for finding the hyperplane that separates the two classes with the maximum margin.

Mathematical Formulation: The mathematical formulation for SVM in binary classification can be expressed as:

minimize:

$$\left(\frac{1}{2}\right) * \left||w|\right|^2 + C * \Sigma\xi_i \tag{3.3}$$

subject to:

$$Y_i * (w^T * X_i + b) \geq 1 - \xi_i, for\ all\ i = 1\ to\ N \tag{3.4}$$
$$\xi_i \geq 0, for\ all\ i = 1\ to\ N$$

In this formulation, the weight vector is denoted by W. perpendicular to the hyperplane, b is the bias term, ξ_i are slack variables, C is the regularization parameter, (X_i) represents the (i-th) sample in the data matrix X, and Y_i is the corresponding emotion label.

Kernel Trick: To handle non-linearly separable data, SVM employs the kernel trick. the incoming data is transformed into a higher-dimensional feature space, the SVM can find a hyperplane that effectively separates the classes. Frequently employed kernels for classifying emotions in EEG data consist of linear, sigmoid, polynomial, and radial basis function kernels.

Multi-Class Classification: SVM is inherently a binary classifier. To extend it for multi-class emotion classification, several strategies can be used, such as “one-vs-one” or “one-vs-rest”.

In one-vs-one, multiple SVM models are trained, each comparing pairs of emotions. In one-vs-rest, separate SVM models are trained for each emotion against the rest.
Training and Prediction: Once the SVM model is trained using the labeled EEG data, it can be used to classify new, unseen EEG samples. The sign of (w^T * X + b) determines the predicted emotion label.

Recurrent Neural Network (RNN):

An RNN “Recurrent Neural Network” is a deep learning network that has a unique structure distinguishing it from other neural networks. Unlike most networks that only consider the current input, an RNN incorporates a "memory" function, allowing it to take into account inputs at any given time. This enables RNNs to process sequential data by retaining information from previous calculations and utilizing it to influence the output of the current input. The RNN structure consists of an input layer, a hidden layer, and an output layer, and it can be combined with other neural networks to extract temporal characteristics from EEG signals. Following feature extraction and selection, the output layer utilizes the Softmax function for classification. RNNs are particularly suitable for processing sequential data, such as continuous natural language or lengthy text sections, as they can remember past calculations and use that information to predict the next segment of the sequence [55].
Esmeralda Contessa Djamal proposed a model for emotional recognition that combines wavelet transform (WT) and RNN to detect emotions such as sadness, relaxation, and pleasure. The model, developed using Python and TensorFlow, employed EEG signals generated by emotional audio and visual stimuli from ten healthy individuals. The researcher converted the EEG readings using WT into brain waves associated with emotions, which were then fed into an RNN model for recognition. EEG data from four channels were collected to ensure the accuracy of the findings. Experimental results demonstrated recognition rates of 92% for sorrow, 53% for relaxation, and 97% for happiness, indicating that the combination of wavelet transform and RNN is a reliable technique for emotion categorization [56].
To categorize emotional aspects in EEG data, Wei Tao proposed a model called ACRNN, which combines CNN (Convolutional Neural Network) and RNN with an attention mechanism. RNN is utilized to capture temporal features, while CNN is employed to extract spatial features. The ACRNN model was trained using EEG and ECG signals generated by emotional stimuli and implemented using Python and TensorFlow. Noise in the EEG

readings was reduced using blind source separation. The ACRNN model, employing the Softmax function in RNN, achieved accurate emotion classification. The research revealed that both the CNN and CNN-LSTM models performed well in extracting emotional features [57].

The mathematical formulation of a Recurrent Neural Network (RNN) involves capturing sequential information and utilizing recurrent connections. Here's an overview of the key mathematical formulations:

Hidden State Update:

In an RNN, the hidden state captures information from previous time steps and influences the current prediction. Updates are made to the concealed state at time step t, represented by "h(t)", and is updated using the input at time step t, denoted by "x(t)", and the previous hidden state, denoted by "h(t-1)". The mathematical calculation for the hidden state update can be expressed as:

$$h(t) = activation\_function(Wxh * x(t) + Whh * h(t-1) + bh) \quad (3.5)$$

Here, "Wxh" represents the weight matrix for the input, Whh represents the weight matrix for the hidden state, and bh represents the bias term. The activation_function is typically a non-linear activation function like tanh or sigmoid.

Output Calculation:

The output of the RNN at each time step is calculated based on the current hidden state. The output at time step t, denoted by y(t), is obtained by applying a weight matrix, Wyh, to the hidden state and adding a bias term by. The mathematical calculation for the output can be expressed as:

$$y(t) = activation\_function(Wyh * h(t) + by) \quad (3.6)$$

Here, "Wyh" is the weight matrix for the output, and by represents the bias term.

Sequence Unfolding:

To process a sequence of inputs, the RNN is typically unfolded over time, creating a series of interconnected RNN cells. Each RNN cell represents a time step, and the hidden state is updated sequentially based on the previous hidden state and the input.

Backpropagation Through Time (BPTT):

Training an RNN involves propagating the error gradient back through time. This process, known as Backpropagation Through Time (BPTT), adjusts the weights and biases to minimize the loss function. BPTT essentially extends the standard backpropagation algorithm to handle the sequential nature of RNNs.

These are the key mathematical formulations for an RNN. Variations of RNNs, such as (LSTM) and (GRU), introduce additional equations and mechanisms to address issues like the vanishing gradient problem and improve the modelling of long-term dependencies.

Convolutional neural network (CNN):

Numerous traditional “machine learning” techniques have been utilized for emotion classification and have shown certain achievements. Nonetheless, such approaches are hindered by certain drawbacks, including challenges encompassing difficulties in extracting features, achieving low accuracy rates, and encountering limited stability. Research indicates that deep learning provides a more effective approach to emotion detection and is particularly suitable for analysing and identifying physiological signals. The use of deep learning in emotion recognition has become increasingly prevalent because of its extraordinary capacity for learning and flexibility. [58]

Convolutional Neural Networks (CNNs) have both advantages and disadvantages when it comes to emotion recognition using EEG signals.

Advantages:

CNNs are effective in identifying patterns in large and complex datasets, which is useful in analysing complex EEG signals for emotion recognition.

They can learn complex feature representations in a hierarchical manner, allowing them to take the raw EEG signals and extract the high-level features.

CNNs can handle the high dimensionality of EEG data effectively, making them suitable for use in emotion recognition tasks.

They are robust to noise and artifacts, which is essential when working with EEG signals that are susceptible to various sources of interference.

Disadvantages:

CNNs require a large amount of labelled data for training, which may be challenging to obtain in the case of EEG-based emotion recognition.

The interpretability of CNNs is limited, making it challenging to understand the features that the network has learned from the EEG data.

They can be computationally expensive, especially when using large datasets and complex network architectures.

CNNs can overfit the training data, which may result in poor generalization to unseen EEG signals.

CNNs are a deep learning algorithm that is particularly well-suited for handling large datasets due to its unique architecture. Unlike traditional artificial neural networks with three layers, CNNs incorporate two additional layers: the pooling layer and the convolution layer. The convolution layer plays a crucial role in extracting relevant features from EEG data and reducing the influence of noise. The pooling layer performs information filtering and feature selection. Once the features are taken out and selected, the fully connected layer combines them as inputs to the output layer, which employs Softmax functions for classification. CNNs consist of numerous neurons organized in a “three-dimensional coordinate system”, allowing for efficient processing of large datasets.[59][60] The CNN structure in figure 3.7.

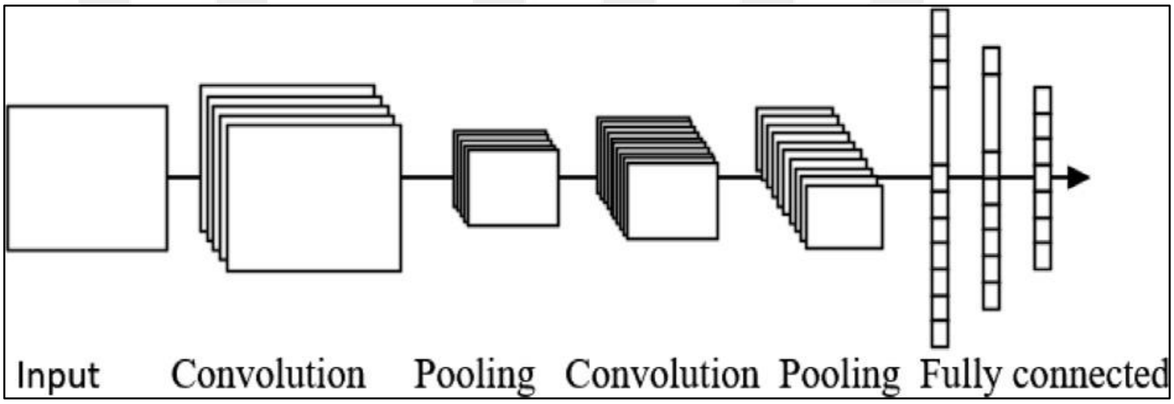

Figure 3.8: CNN Structure [54].

Heekyung Yang's proposal for sentiment recognition is a multi-column CNN model which includes multiple recognition units whose primary reliance is on one-dimensional clustering and convolution layers CNN. In their study, the researchers used the DEAP dataset as experimental data, which was preprocessed by reducing the frequency and analysing and sampling EEG signals with a pandpass filter multiple times. The preprocessed data was then utilized as input for the recognition module. The model used a weighted averaging of the decisions made by each module to ensure accurate recognition results. The model code was implemented using Python and Pytorch libraries. Trial results revealed that the model achieved a high valence rate of 90.01% and arousal rate of 90.65%. [55][61]

Here's a brief explanation of the mathematical components involved in CNNs for EEG-based emotion classification:

Convolution Operation: The convolutional operation is a fundamental component of CNNs. It involves sliding a filter (also known as a kernel) over the input EEG data, performing element-wise multiplication, and summing the results to generate feature maps. The mathematical calculation for a convolution operation:

$$FeatureMap[i, j] = sum(Input[i + k, j + l] * Filter[k, l]) \tag{3.7}$$

Activation Function: After each convolutional operation, an activation function is applied elementwise to introduce non-linearity. Common activation functions used in CNNs include Rectified Linear Unit (ReLU), sigmoid, or hyperbolic tangent (tanh) functions.

Pooling Operation: The pooling process preserves the most prominent features and reduces the spatial dimensions of feature maps. Max pooling is commonly used in CNNs, where the maximum value within each pooling region is selected. The mathematical process of max pooling can be represented as:

$$PooledFeatureMap[i, j] = \max(FeatureMap[i + k, j + l]) \tag{3.8}$$

In a fully connected layer, the extracted features from the previous layer are passed through a set of neurons, where each neuron is connected to every neuron in the previous layer. The calculation in a fully connected layer can be represented mathematically as follows:

$$Output[i] = activation\_function(sum(Weight[i, j] * Input[j]) + Bias[i]) \tag{3.9}$$

The Softmax activation function is commonly used in the final layer of a neural network for multi-class classification tasks, such as emotion classification. It takes the raw output values from the previous layer and transforms them into a probability distribution over the different classes:

$$P(class\ i) = \frac{exp(Output[i])}{sum\big(exp(Output[j])\big)}\ for\ all\ classes \tag{3.10}$$

Loss Function and Optimization: The choice of loss function depends on the specific problem. For multi-class classification, cross-entropy loss is commonly used. The CNN is trained by optimizing the weights and biases to minimize the loss using optimization algorithms such as stochastic gradient descent (SGD), Adam, or RMSprop.

The above mathematical components are combined to create a CNN architecture for emotion classification using EEG data. The architecture may vary depending on the specific requirements and complexity of the task. Additionally, data preprocessing, data augmentation, regularization techniques, and hyperparameter tuning are essential aspects to consider for achieving optimal performance in CNN-based emotion classification systems.

Long Short-Term Memory Network (LSTM):

A long-term memory network is an advanced “recurrent neural network that can store information for lengthy periods of time, unlike RRNs in the fading gradient problem”, it can handle it based on data. The network maintains its long-term dependencies through its gate mechanisms. In the network, memory can be stored or released depending on the destination, depending on the gateway mechanism. Gates can be described as the three basic components of an LSTM cell [62] [63]. The first section is the Oblivion Gate, the second section is the input gate, and the third section is the output, as shown in the figure below.

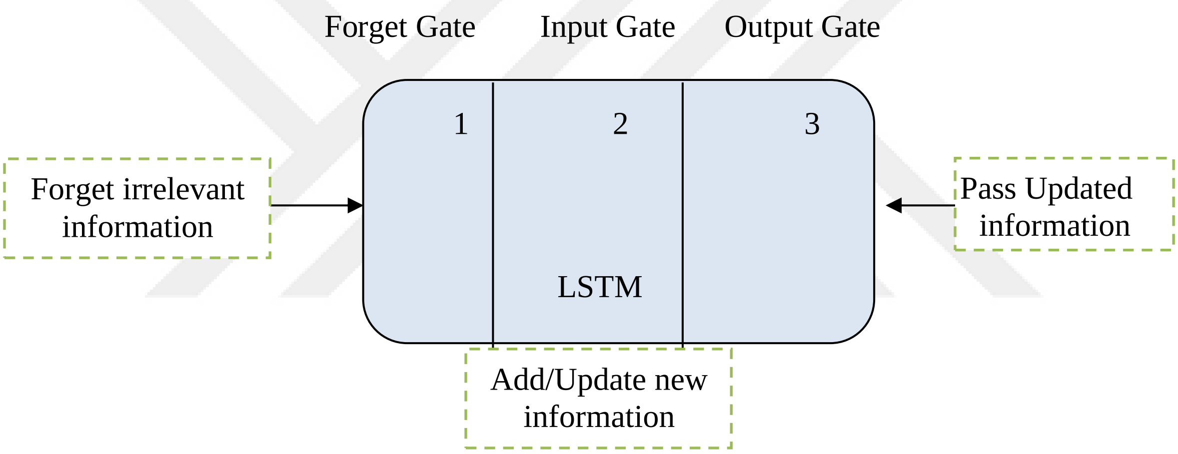

Figure 3.9: LSTM Cell with Gates.

The LSTM structure as in the simple RNN structure contains a hidden state. Where Ht - 1 traverses the hidden state of the previous time, and Ht traverses the hidden state at the present time. It also contains the state of the cell, which is represented by Ct and Ct - 1, respectively, for the current and past time states [64][65].

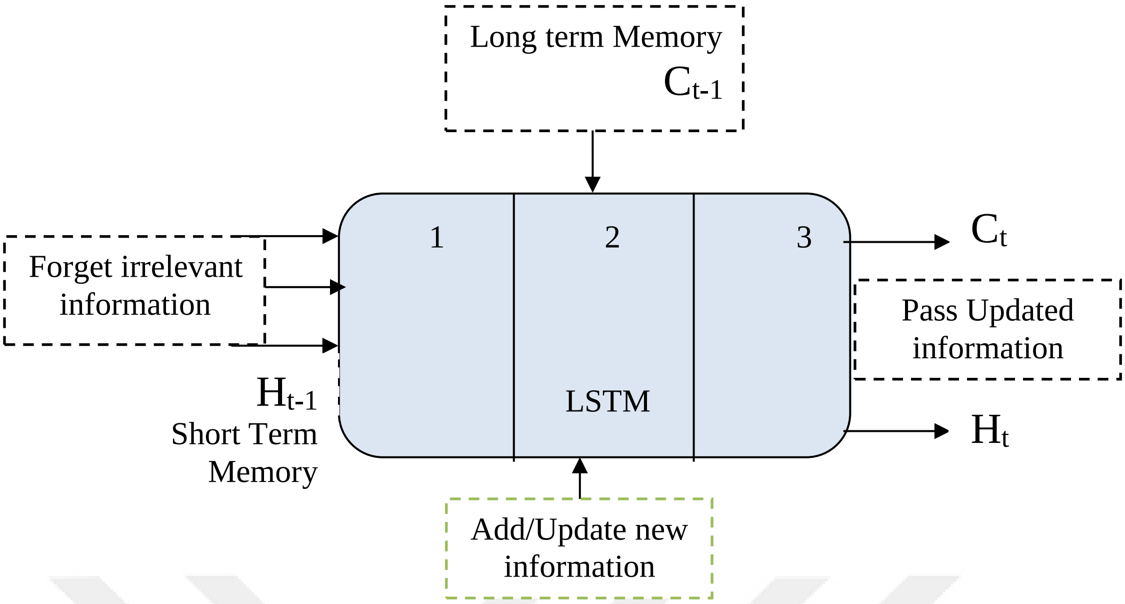

Figure 3.10: LSTM Cell with Hidden and Cell States

Oblivion Gate: It is considered the first gate of the gates. All old memories pass through when this portal opens fully. when closed, no previous memories will be saved. It consists of multiplying one element with another. The forgetting gate equation can be expressed as follows:

$$f_t = \sigma(X_t * U_f + H_{t-1} * W_f) \tag{3.11}$$

To erase most of the old memory, multiply the old memory by a vector close to zero. Whereas, when setting the forgetting gate to the value of 1, this allows the old memory to pass through, as in the following equation:

$$C_{t-1} * f_t = 0(if\ f_f) = 0 \tag{3.12}$$

$$C_{t-1} * f_t = C_{t-1}(if\ f_f) = 1 \tag{3.13}$$

When Xt and Ht-1 insert the current timestamp and the hidden state of the previous timestamp. While expressing the weights associated with the entries and hidden states Uf and Wf.

Entry gate: It is considered the second gate. Specifies the number of new entries that should be allowed in. It is assumed that new and old memories will be affected differently by modifying this gate. This gate is used to measure the importance of the new data that the entry holds. The equation for this gate is as follows:

$$i_t = \sigma(X_t * U_i + H_{t-1} * W_i) \quad (3.14)$$

Where Wi and Ui express the weights associated with the current entries and the previously hidden layers.

Cell case: The plural comes after that, which is a discontinuous plural. This process mixes the old memory and the current input. To form St. Addition in terms of elements is used for the current input and the old memory.

$$\overline{C_t} = tanh(X_t * U_c + H_{t-1} * W_c)(New\ information) \quad (3.15)$$

$$C_t = f_t * C_{t-1} + I_t * \overline{C_t}\ (Updating\ Cell\ State) \quad (3.16)$$

Output Gate: Generate output for the LSTM module. The new memory and the current input and the previous output all control the output gate in this stage. This gate regulates the amount of new memory that should be sent to the next LSTM unit.

$$O_t = \sigma(X_t * U_O + H_{t-1} * W_O) \quad (3.17)$$

To determine the current hidden state the modified cell states Ot and tanh are used. And given the sigmoid function, its value will also be between 0 and 1.

$$H_t = X_t * tanh(C_t) \quad (3.18)$$

The function for current output and long-term memory (Ct) is the hidden state. The SoftMax activation function is applied to the hidden state Ht if there is a need to get the current timestamp output.

$$Output = Softmax(H_t) \quad (3.19)$$

Gated Recurrent Network (GRU):

GRU is similar to LSTM but has fewer gates and is a variant of the RNN architecture where gates are used to control the flow of information between neurons. It also relies on the hidden state to transfer memory between redundant units. Compared to LSTM, it is new and thus surpasses it with its clearer structure[66].

One hidden state is passed from a one-time step to another in GRUs. As a result of the gate mechanisms, calculations are performed on the input data and the hidden state. It is also distinguished by its ability to maintain short and long-term dependencies at the same time. Applications of GRU architecture are speech recognition, stock price prediction, sentiment analysis, machine translation, etc. The following figure shows the structure of the GRU.

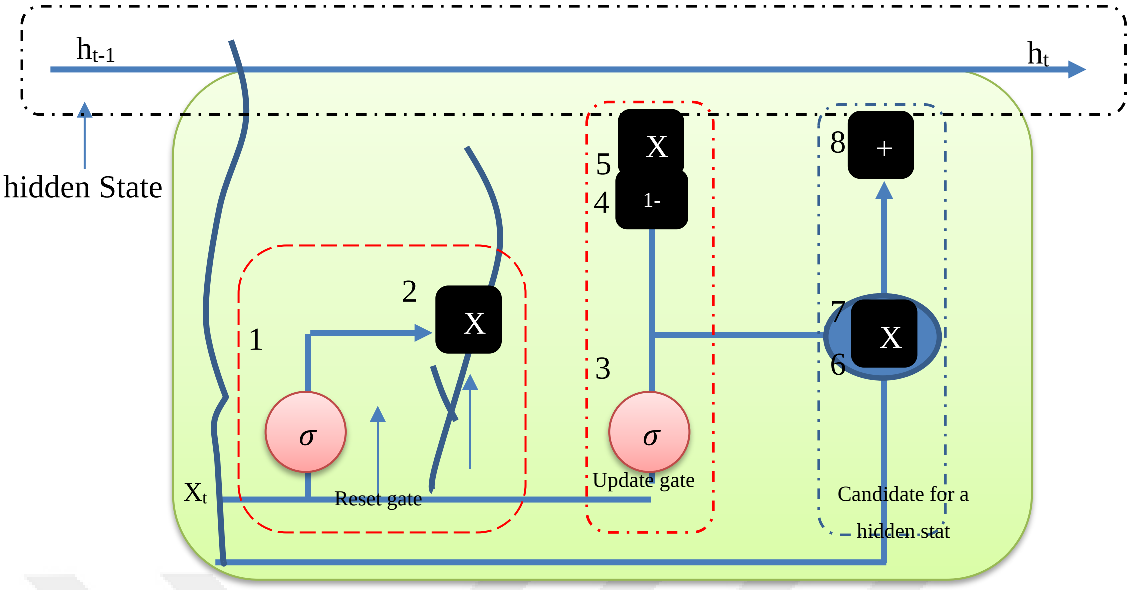

Figure 3.11: GRU Recurrent Unit.

1-2) Reset gate: The current input (x_t) and the former hidden state (h_t-1) are multiplied by their respective weights and then transferred together through the reset gate. The first step determines which values to ignore (0), remember (1), or partially keep (between 0 and 1) because the sigmoid function has a range of 0 and 1. The previous hidden state is reset in the second step by multiplying it by the results of the first step.

$$r_t = \sigma(X_t * U_r + H_{t-1} * W_r) \tag{3.20}$$

In the hidden case in (3–4–5), although the third step of the update gate may appear similar to the first step in some respects, the weights and biases used to measure these vectors are different, resulting in a characteristic sigmoidal output. As a result, in the fourth step, we subtract the complex vector from the vector containing 1 and multiply it by the sigmoid function (the previous hidden case). (Step 5). This is a component of updating the hidden state with new data.

$$U_t = \sigma(X_t * U_u + H_{t-1} * W_u) \tag{3.21}$$

6-7-8) The outputs are mixed with the new inputs (x_t), multiplied by their respective weights, and biases are added before going through the tanh activation function (6th step). This is done after resetting a previous hidden state in step two. The state is generated The new hidden state h_t multiplies the hidden state filter by the update gate output (step 7) and combines it with the previously changed hidden state h_t - 1. Once the iterative unit has processed the complete sequence, the process is then repeated for the time step t + 1 and subsequent time steps.

$$\bar{h} = tanh(X_t * U_h + r_t * h_{t-1} * W_h). \tag{3.22}$$

$$h_t = U_t * h_{t-1} + (1 - U_t) * X_t * \bar{h} \tag{3.23}$$

where ht indicates the current hidden state

Architecture by GRU

The gated recurrent unit, or GRU for short, uses the same process as an RNN but uses different gate operations. The update gate and the reset gate, which are described [67], are two gates that GRU incorporates to solve the ordinary RNN problem. The figure explains the GRU cell's internal construction.

The GRU method utilized in this study is made up of three layers: a flattened layer, a dense layer with softmax activation, and a GRU layer with 256 units. Raw EEG signals are used to extract learning features, which are then classified into emotions using a dense layer and the GRU layers. The GRU model for EEG-based emotion recognition employed in this investigation is shown in Figure 15.

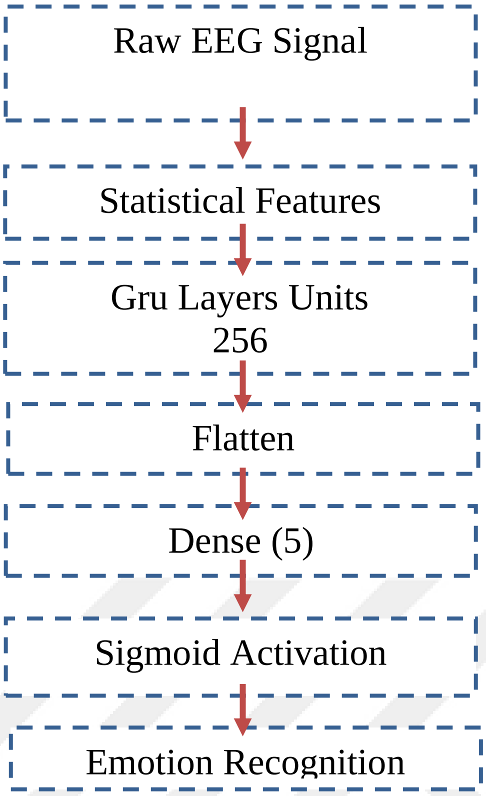

Figure 3.12: Detailed GRU Model.

Algorithms comparison:

Support Vector Machines (SVM), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and Gated Recurrent Units (GRU) are all commonly used algorithms for emotion recognition in EEG signals. Here's a comparison of their strengths and weaknesses:

a. SVM:

a. Strengths: Can handle high-dimensional data with a limited number of samples, effective in binary classification tasks, can handle non-linear data through the use of kernel functions, good at capturing non-linear decision boundaries.

b. Weaknesses: Limited ability to capture temporal dynamics, computationally expensive for large datasets, requires careful selection of kernel functions and hyperparameters.

b. CNN:

a. Strengths: Effective in capturing spatial and temporal features, automatically learns relevant features from raw data, reduces the need for manual feature engineering, suitable for large-scale datasets, widely used in image and signal processing tasks.

b. Weaknesses: Requires large amounts of labelled data, computationally expensive for complex architectures and large datasets, may overfit with insufficient regularization.

c. RNN:

a. Strengths: Can model sequential data and capture temporal dependencies, flexible in handling inputs of varying lengths, suitable for real-time processing, widely used in natural language processing and speech recognition.

b. Weaknesses: Suffers from the vanishing/exploding gradient problem, limited ability to capture long-term dependencies, computationally expensive due to sequential processing, and difficult to parallelize.

d. LSTM:

a. Strengths: Specifically designed to address the vanishing gradient problem, effective in capturing long-term dependencies, retains memory over long sequences widely used in various sequence modelling tasks, such as speech recognition and language translation.

b. Weaknesses: Computationally expensive, requires large amounts of labelled data, may overfit with insufficient regularization can be difficult to interpret.

e. GRU:

a. Strengths: Similar to LSTM, captures long-term dependencies, is faster to train due to fewer parameters, uses gating mechanisms to selectively update and forget information can handle sequence-to-sequence learning tasks.

b. Weaknesses: May still suffer from the vanishing gradient problem, requires careful tuning of hyperparameters, may overfit with insufficient regularization.

In summary, each algorithm has its own strengths and weaknesses, and the choice depends on the specific requirements of the problem at hand. SVM is suitable for binary classification and handling high-dimensional data. CNN is effective in capturing spatial and temporal features from raw data. RNN and LSTM are suitable for modelling sequential data, while LSTM excels at capturing long-term dependencies. GRU offers a balance between computational efficiency and capturing temporal dynamics. The selection should consider factors such as the nature of the data, available computational resources, and the desired trade-off between model complexity and performance.

3.3.10 Classification

The classification was performed using five different machine-learning algorithms. “Gaussian Naïve Bayes classifier, support vector machine, logistic regression, decision tree classifier, and random forest”.

After that, the model is trained for each classifier on (X_train, Y_train) data, and then predictions are made for the test data (X_test) and the classification is printed, which includes accuracy, recall, F1 score, and support for each separately. In addition, the confusion matrix is calculated and drawn using the Confusion Matrix.

Finally, a classification report was printed for the deep learning model (GRU & CNN) that was previously trained on the same dataset and compares the results of all classifiers.

Then the trained GRU & CNN model was saved to a file so that new predictions are performed on the new data in real-time. Doing that, the classification process has been completed for the dataset after collecting, naming, and processing it.

3.3.11 Predict the Emotion in Real Time

After training the model and classifying the emotions on the EEG dataset, this trained deep learning model was used to classify and predict the emotions on new EEG data in real-time. This study focuses also on the real-time prediction of emotions using a pre-trained model. The model, previously trained on a suitable dataset, is loaded to make predictions on incoming data. The real-time data, obtained in CSV format, is preprocessed to remove irrelevant columns and normalize the brain signals. Preprocessing includes encoding emotion labels into numerical values and scaling the brain signals using StandardScaler.

After preprocessing, the pre-trained model is used to predict the emotions associated with the input data. The model's predictions are obtained by applying the argmax function to the model's output, resulting in the most probable emotion for each input. These predicted emotions are then assigned back to the data.

To determine the prevailing emotion from the predictions, the code calculates the frequency of each emotion. The emotion with the highest frequency is considered the most likely emotion and is printed accordingly ("Happy", "Angry", "Calm", "Neutral", or "Sad").

This approach enables real-time emotion prediction by utilizing a pre-trained model and applying it to incoming data. By incorporating appropriate preprocessing techniques and leveraging the model's prediction capabilities, it offers a practical and efficient method for emotion recognition in real-world scenarios.

4. RESULTS

4.1 DATASET

There are many datasets of EEG signals extracted from high-resolution devices and processed. In this project, no ready-made dataset was relied upon, and models and methods were tested. A dataset was generated from scratch using the MINDWAVE MOBILE device. Then, this data was processed by applying some preliminary processing operations. This dataset contains 11 columns “Raw, Attention, Meditation, delta, theta, low-alpha, high-alpha, low-beta, high-beta, low-gamma, mid-gamma” and 3000 rows. These data were first imported separately for each emotion trait by supervised methods. Then this data had compiled into a single dataset file and add the sentiment field during the labeling process. Then pre-processed before undergoing training by the classification algorithms. Although it is great to create a new dataset, especially in our project, there are some disadvantages, including the device's limitations in capturing signals. This means that it is difficult to increase the shapes, and this causes the dataset to be weak in processing and the algorithm has difficulty in classifying the data. In contrast to the ready-made datasets published on websites, in which the number of forms may reach 1000 columns. And since our project supports the classification of emotions in real-time, it may be assumed to use a dataset that is generated through the same device used and has the same number of shapes when training the model. This helps classify emotions in real-time. Although this dataset has few forms, good results were obtained during the training of the model compared to some results of models that were trained on a ready-made dataset. The strength of our study also lies in the creation of a new dataset and support for the classification of emotions in real-time. The following table shows the signals of the trained dataset:

Table 4.1: EEG Signals Dataset After Combination and Labels Them.

ID	Raw	Attention	Meditation	….	Low gamma	Mid gamma	Emotion
0	58	54	75	….	1508	236	angry
1	0	81	41	….	534	491	angry
2	109	51	61	….	4638	2059	sad
3	69	64	94	….	2212	297	neutral
4	60	21	66	….	4271	1194	angry
….	….	….	….	….	….	….	….
2995	8	87	81	….	1988	2023	neutral
2996	84	93	51	….	3093	6376	sad
2997	75	56	63	….	188	226	calm
2998	128	4	69	….	355	291	calm
2999	55	78	54	….	205	537	sad

[3000 rows x 12 columns]

4.2 MODEL

Emotion recognition is a complex field in artificial intelligence, and achieving high accuracy in classifying emotions from data is crucial for its successful integration into AI systems. In our study, we focused on enhancing emotion recognition through the implementation of advanced neural network models. We explored the capabilities of a custom-designed model and compared its performance to traditional machine learning classifiers.

Each classifier has its own weaknesses and strengths, the choice depends on the specific requirements of the problem at hand. SVM is suitable for binary classification and handling high-dimensional data. CNN is effective in capturing spatial and temporal features from raw data. RNN and LSTM are suitable for modeling sequential data, while LSTM excels at capturing long-term dependencies. GRU offers a balance between computational efficiency and capturing temporal dynamics. The selection should consider factors such as the nature of the data, available computational resources, and the desired trade-off between model complexity and performance.

The classification was performed using five different machine-learning algorithms. “Gaussian Naïve Bayes classifier, support vector machine, logistic regression, decision tree classifier, and random forest”, addition to algorithms that was mentioned first.

The model has trained for each classifier on (X_train, Y_train) data, and then predictions was made for the test data (X_test) and the classification is printed, which includes accuracy, recall, F1 score, and support for each separately. In addition, the confusion matrix was calculated and drawn using the Confusion Matrix.

The scales used to estimate the output of the proposed model depend on the target task, which is sentiment rating. The accuracy of training and testing the neural network before and after applying the feature selection method was estimated.

For the comparative study, we compared the outputs of the neural network classification methods each time the model was trained in a different way, extracted the results, compared them, and worked on improving them. The results were classified according to the method used in the trained model. The proposed work is implemented using the Python programming language.

GRUs outperform LSTMs with less training data, especially when used for language modeling applications. GRUs are simpler and contain less code when the network requires additional inputs because they are easier to change. Model summaries show that GRUs also have lower parameters than LSTM.

The below figure shows the results of the initial training in the testing phase of the model before optimizing the model. Therefore, the results show us the instability in both the loss function diagram and the validation function of the LSTM model.

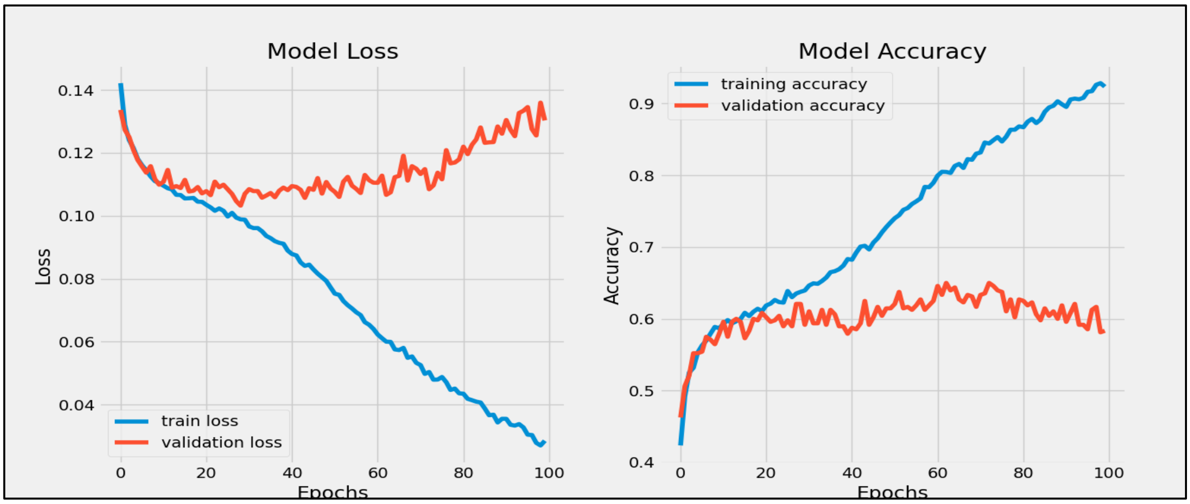

Figure 4.1: LSTM Training Results.

Due to the efficiency of the GRU, which distinguishes it from the LSTM, the GRU was used in the second training process. The GRU model has 212,997 total parameters with 256 internal units. The results showed an advantage in accuracy and loss. The below figure representation of the GRU model's input and output vector shapes is provided in the table along with a Keras implementation of the GRU architecture.

Table 4.2: Keras Implementation of the GRU Architecture.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 11)]	0
tf.expand_dims (TFOpLambda)	(None, 11, 1)	0
gru (GRU)	(None, 11, 256)	198912
flatten (Flatten)	(None, 2816)	0
dense (Dense)	(None, 5)	14085
Total params: 212,997		
Trainable params: 212,997		
Non-trainable params: 0		

Input_5: inputLayer	Input	[(None, 11)]
	Output	(None, 11)

Tf.Expand_dims_2: TFOpLambda	Input	[(None, 11)]
	output	(None, 11, 1)

Gru: GRU	Input	(None, 11, 1)
	output	(None, 11, 256)

Flatten_2: Flatten	Input	(None, 11, 256)
	output	(None, 2816)

Dense_2: Dense	Input	(None, 2816)
	Output	(None, 5)

Figure 4.2: With Input and Output Vector Forms, the GRU Architecture has Been Detailed.

After using GRU instead of LSTM, the results showed some improvement in both accuracy and loss as shown in the figure below.

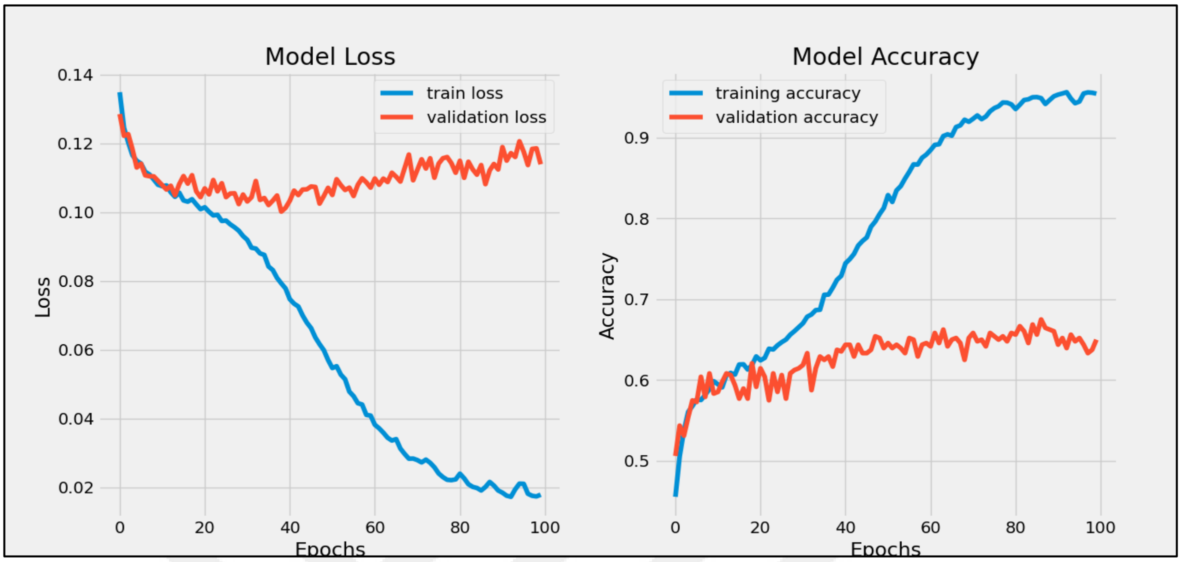

Figure 4.3: GRU Training Results.

The results may not conclusively depend on the type of algorithm used only in the process of training the sentiment rating model. There are other effects that improve results and increase classification accuracy in particular. These effects can be the increase in the number of input units of the algorithm, and the use of multiple algorithms at the same time. Increase the number of seeds. After training the prototype with the GRU, it worked when adding a one-dimensional convolutional neural network to the GRU.

Table 4.3: Keras Implementation of the 1D CNN & GRU Architecture.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 11)]	0
tf.expand_dims (TFOpLambda)	(None, 11, 1)	0
conv1d (Conv1D)	(None, 9, 64)	256
gru (GRU)	(None, 9, 256)	247296
flatten (Flatten)	(None, 2304)	0
dense (Dense)	(None, 5)	11525
Total params: 259,077		
Trainable params: 259,077		
Non-trainable params: 0		

The training above shows that a 1D convolutional layer with 64 filters and a kernel size of 3 is added before the GRU layer. The activation function used in the convolutional layer is 'relu'. The output of the convolutional layer is passed to the GRU layer for further processing. The rest of the architecture is the same as before.

The main difference between 1D CNN and 2D CNN lies in the type of input data they are designed to process.

a. D CNN: A 1D CNN is typically used for sequential or time series data, where the input data has a sequential order and each data point has one-dimensional features. It operates on a one-dimensional input, such as a signal or a time series. The convolution operation in 1D CNN is performed along the time axis or sequence axis.

b. D CNN: A 2D CNN, on the other hand, is designed for grid-like data, such as images or spectrograms, where the input data has two-dimensional features. It operates on a two-dimensional input grid, such as an image represented by pixels arranged in rows and columns. The convolution operation in 2D CNN is performed across both the height and width dimensions of the input.

In summary, the key distinction is that 1D CNN is suitable for sequential data, while 2D CNN is suitable for grid-like data, such as images. The choice between 1D CNN and 2D CNN depends on the nature of the input data and the specific task at hand.

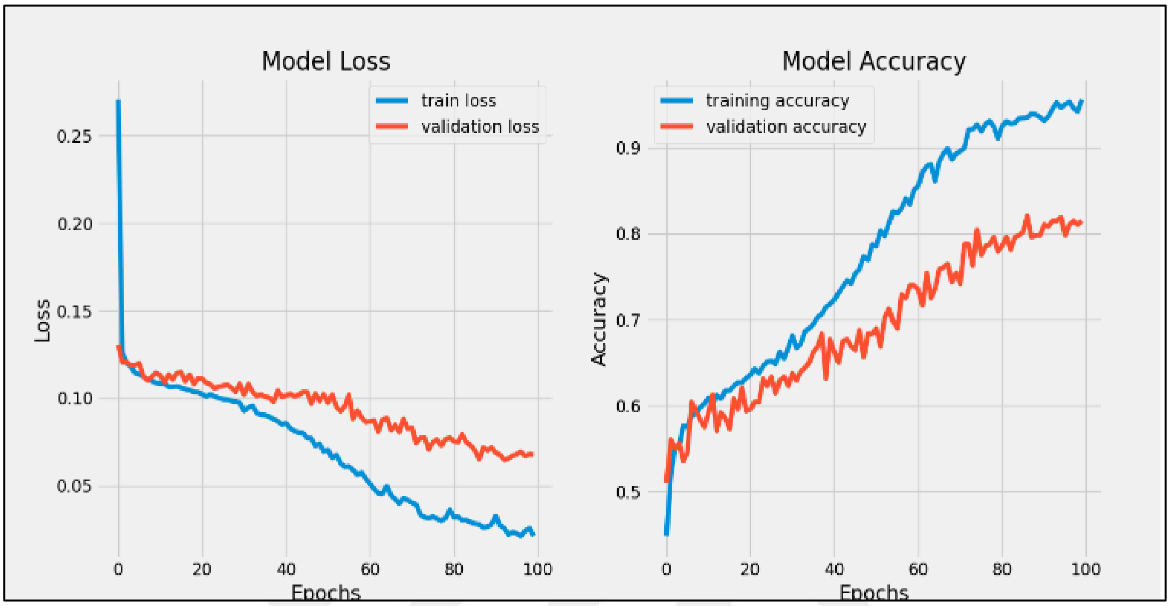

Figure 4.4: GRU & 1D CNN Training Results.

In this thesis, we propose a novel architecture for emotion recognition in EEG signals by combining multiple 1D "Convolutional Neural Network (CNN) layers with a Gated Recurrent Unit (GRU)". The architecture aims to leverage the strengths of both CNNs and GRUs to effectively capture and model the complex temporal dynamics present in EEG data. The first part of our architecture consists of two consecutive 1D CNN layers. The initial CNN layer, denoted as `conv`, comprises 512 filters with a kernel size of 3. This layer is responsible for learning 512 different patterns or features from the input EEG signals. We apply the "Rectified Linear Unit (ReLU) activation function" to introduce non-linearity into the output of this layer. Subsequently, we add another CNN layer, referred to as `conv1`, with 256 filters and a kernel size of 5. This layer further extracts spatial and temporal features from the output of the previous CNN layer using the ReLU activation function.

Following the CNN layers, we incorporate a GRU layer, denoted as `gru`, to capture the temporal dependencies within the extracted features. The GRU layer consists of 512 units and is designed to maintain both short-term and long-term dependencies. By setting `return_sequences=True`, the GRU layer outputs the full sequence of hidden states, enabling the model to capture the sequential information present in the EEG signals. Moreover, we apply L2 regularization with a coefficient of 0.001 to the GRU layer using the `kernel_regularizer` parameter, which helps prevent overfitting and improves the generalization capability of the model.

The combination of multiple 1D CNN layers and a GRU layer in our proposed architecture allows for the extraction of hierarchical features from the EEG signals and the modeling of their temporal dependencies. This enables the model to effectively recognize and classify emotions embedded in the EEG data. The proposed architecture holds great potential for enhancing emotion recognition systems in various domains, including healthcare, affective computing, and human-computer interaction.

Usually a combination of multidimensional CNN layers and a GRU layer:

a. Multiple 1D CNN Layers: Each CNN layer performs convolution operations on the input data, capturing local patterns and extracting relevant features. The CNN layers can have different filter sizes, strides, or other parameters to extract features at different scales or levels of abstraction. The output of each CNN layer will be a set of higher-level features.
b. GRU Layer: The output of the last CNN layer is then fed into the GRU layer. The GRU layer is a type of recurrent neural network layer that can capture the temporal dependencies in the sequence of input features. It maintains a hidden state that remembers information from previous time steps and uses it to influence the current prediction.

By combining multiple 1D CNN layers with a GRU layer, the model can learn both local and temporal patterns in the input data. The CNN layers capture local patterns in the features extracted from the input data, while the GRU layer captures the temporal dependencies between these features. This combination can be particularly useful for tasks that require both local and sequential information, such as speech recognition, gesture recognition, or music analysis.

It's important to note that the specific architecture, number of CNN layers, and hyperparameters can vary depending on the dataset and task. Experimentation and fine-tuning are often necessary to achieve optimal performance.

Table 4.4: The Architecture of the Training Multi 1D CNN with One GRU.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 11)]	0
tf.expand_dims (TFOpLambda)	(None, 11, 1)	0
conv1d (Conv1D)	(None, 9, 512)	2048
conv1d (Conv1D)	(None,5, 256)	655616
gru (GRU)	(None, 9, 512)	1182720
flatten (Flatten)	(None, 2560)	0
dense (Dense)	(None, 5)	12805
Total params: 1,853,189		
Trainable params: 1,853,189		
Non-trainable params: 0		

Upon closer inspection, we observed the following predictions and actual labels for a subset of test samples:

-Predicted Emotions: [0 3 0 3 2 4 3 2 4 4]

-Actual Emotions: [0 3 0 3 3 1 3 4 0 4]

then has been analyzed the confusion matrix to gain insights into the model's performance. Notably, the confusion matrix for our custom model, as well as traditional machine learning classifiers.

Custom Neural Network Model (GRU & CNN)

[90	4	5	7	8]
[6	107	0	5	8]
[6	0	96	10	4]
[8	9	6	105	5]
[7	9	3	4	88]

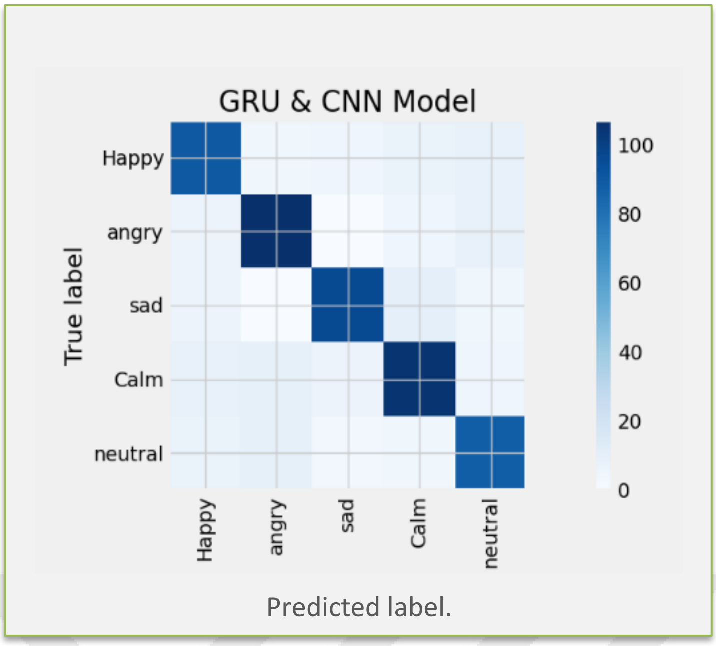

Figure 4.5: GRU & Multi 1D CNN Convolution Matrix.

The Figure shows that the confusion matrix plot visually displays the model's classification performance. Each cell represents the number of correct and incorrect predictions for each category. Where the horizontal labels are the predicted labels and the vertical features are the true labels that are supposed to be correct. The colour intensity shows the size of these counts. The greater the intensity of the blue colour, the more accurate the model is in classification and prediction. The results in Figure 8 above showed great distinction in classification, as each feature was given a high color intensity and was consistent between the predicted labels and the true labels.

In contrast to the following Figure 9, which shows the extent of dispersion of colours in the confusion matrix, which means that the classification results are weak for this algorithm when working on it, this algorithm was tested to clarify the extent of the difference in the confusion matrix diagram when the algorithm gives high classification accuracy and when the accuracy is low.

Gaussian Naive Bayes

[31	7	60	3	13]
[9	46	24	8	39]
[10	3	98	0	5]
[14	19	58	13	29]
[18	5	43	5	40]

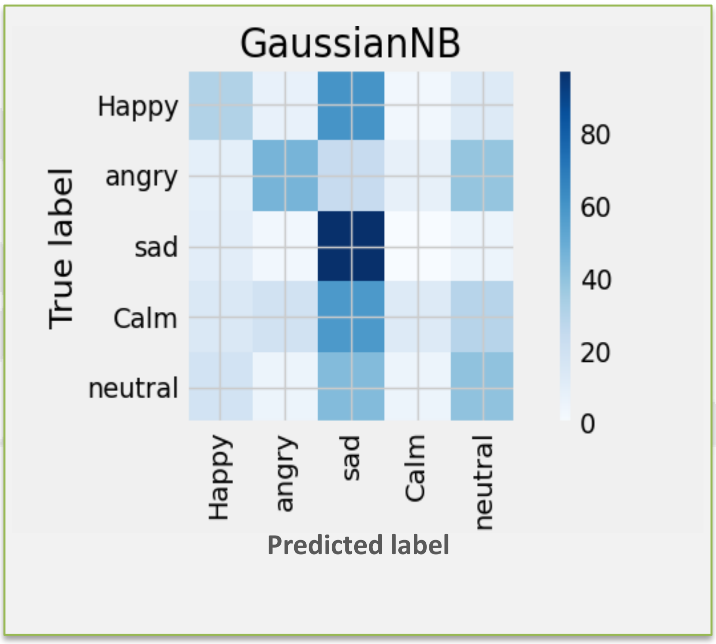

Figure 4.6: Gaussian NB Convolution Matrix.

When the confusion matrix is as in Figure 9, the real-time prediction will give wrong results, as most of the time reading the sentiment data will give the sad emotion. The reason is that the dominant characteristic and intensity of the colour is due to emotion of sad.

But we notice in Figure 10 that the confusion matrix of the SVM algorithm in classification results better than GaussianNB, but we also notice from the figure that the happy state in true label gives similar results to the sad state when predicting. This is called confusion when predictive label.

This is also the case in Figure 11, which describes the Logistic Regression technique, where the results are similar to SVC.

Support Vector Machine

[36	7	38	15	18]
[5	69	7	21	24]
[11	5	84	9	7]
[10	34	18	59	12]
[10	13	22	17	49]

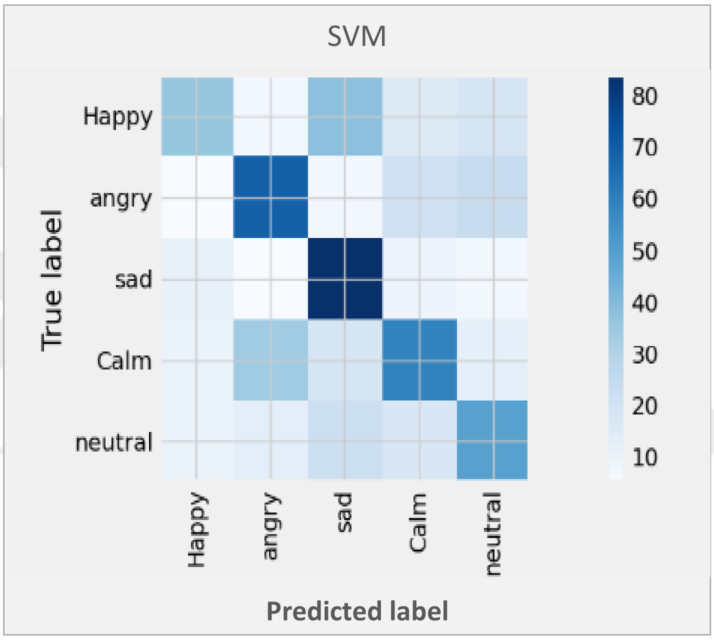

Figure 4.7: SVM Convolution Matrix.

Logistic Regression

[35	5	39	11	24]
[10	70	6	17	23]
[15	3	83	7	8]
[12	35	17	58	11]
[10	21	20	13	47]

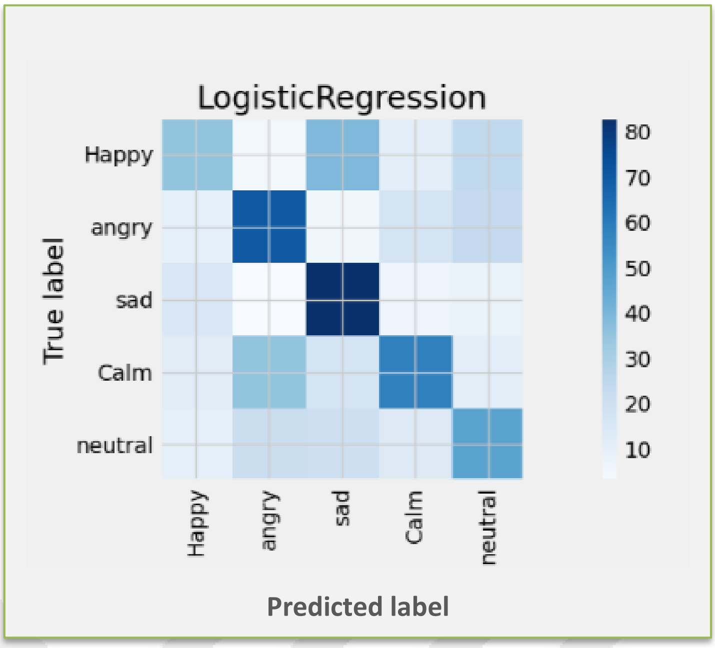

Figure 4.8: LR Convolution Matrix.

Random Forest

[102	2	4	2	4]
[3	118	0	2	3]
[4	2	104	6	0]
[3	17	2	110	1]
[9	6	0	0	96]

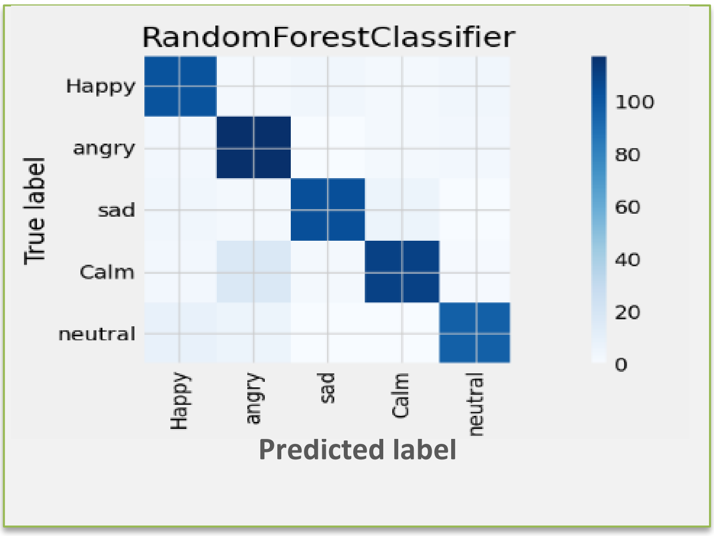

Figure 4.9: RFC Convolution Matrix.

Finally, a classification report was printed for the deep learning model (GRU & CNN) that was previously trained on the same dataset and compares the results of all classifiers (Table 3).

The classification report for our Brain Waves GRU & CNN model provides a comprehensive evaluation of its performance in emotion recognition. It reveals precision values ranging from 0.77 to 0.87 across different emotion categories, highlighting the model's ability to make accurate predictions. Moreover, the recall scores, ranging from 0.79 to 0.85, underscore the model's capacity to effectively capture true positive instances. The F1-score, a harmonic mean of precision and recall, demonstrates strong values, ranging from 0.78 to 0.85, indicating a balanced trade-off between precision and recall. Overall, the model achieves an impressive accuracy of 84% on a dataset of 600 samples, reflecting its robustness in classifying emotions. The macro-average and weighted-average metrics further support the model's consistency, reliability and superiority over other algorithms, including LSTM, with macro-average values of 0.81, highlighting a balanced performance across emotion categories. These results affirm the model's potential for applications requiring precise emotion recognition.

Table 4.5: Classification Report of Brain Waves GRU & Multi 1D CNN.

	Precision	Recall	F1-Score	Support
0	0.77	0.79	0.78	114
1	0.83	0.85	0.84	126
2	0.87	0.83	0.85	116
3	0.80	0.79	0.80	133
4	0.78	0.79	0.79	111
Accuracy			0.81	600
Macro avg	0.81	0.81	0.81	600
Weighted avg	0.81	0.81	0.81	600

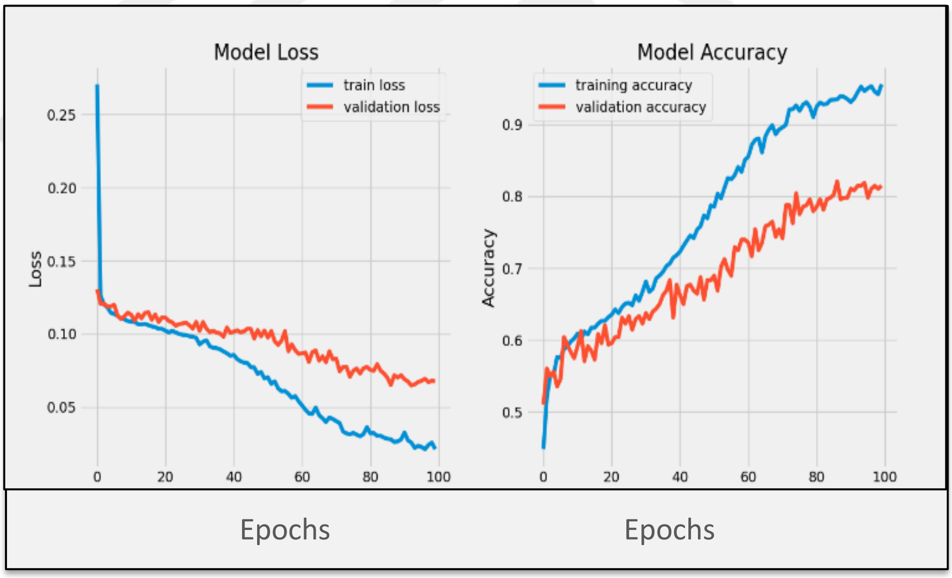

Figure 4.10: GRU & Multi 1D CNN Training Results.

The results of our experiment were promising, with the custom neural network model achieving an accuracy of 84% on the training dataset as figure 4.10 showed. While. However, it is essential to assess the model's performance on unseen data. On the testing dataset, our model reported a loss of 7.2959 and an accuracy of 84%, demonstrating its ability to generalize well to new, previously unseen data. It is superior to other classifiers, including LSTM, the accuracy results were 67% Figure 4.11 shows this.

Then the trained GRU and CNN model was saved to a file so that new predictions are performed on the new data in real-time. Doing that, the classification process has been completed for the dataset after collecting, labeling, and processing it.

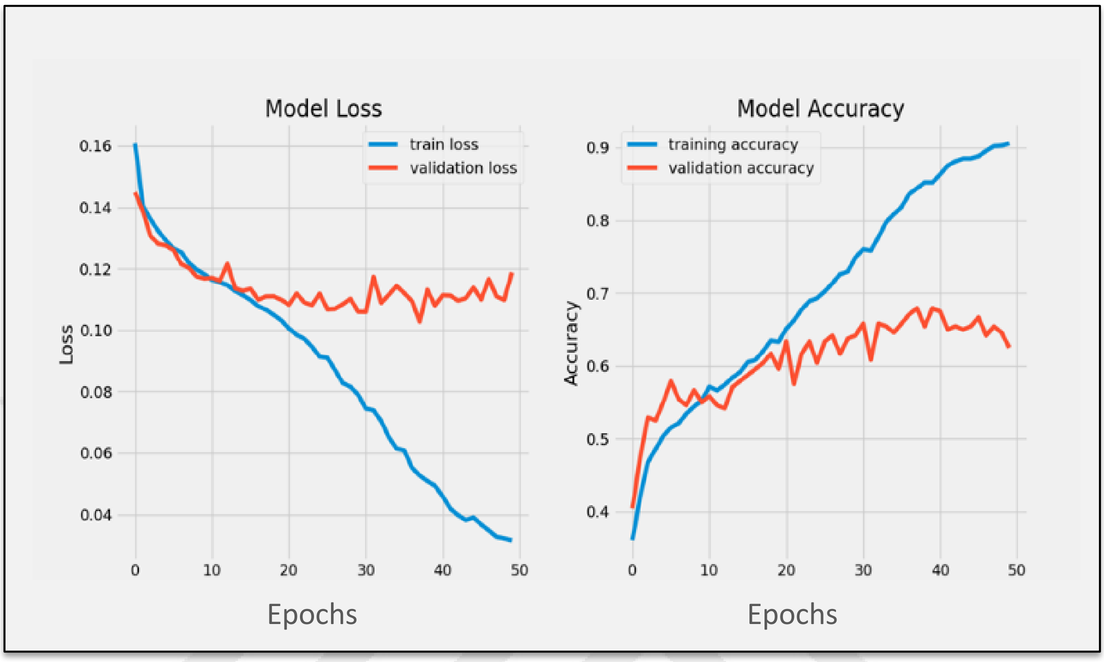

Figure 4.11: LSTM Training Results.

Table 4.6: Results of Each Method Trained Alone.

Method	Epoch	Loss	accuracy	Val Loss	Val accuracy	Loss on testing	Accuracy on testing
LSTM	1	0. 1422	0.4235	0.1337	0.4625	12.521	61.050
	100	0.0285	0.9235	0. 1303	0. 5833		
GRU	1	0.1351	0.4639	0.1342	0.4417	12.124	63.719
	100	0.0188	0.9516	0.1209	0.6333		
GRU & 1D CNN	1	0.0333	0.9108	0.0730	0.7812	8.093	76.063
	100	0.0809	0.7606	0.7932	0.7203		
GRU & Mul-CNN	1	0. 1928	0.4599	0.1290	0.5104	6.644	84.984
	100	0.0172	0. 9625	0. 0679	0. 8283		

5. DISCUSSION AND CONCLUSIONS

5.1 CONCLUSIONS

This study illuminates the proficiency of advanced neural networks in emotion recognition tasks, discussing the intricate process of recognizing emotions using MindWave (EEG) signals and deep neural networks. The process encompasses several stages including data collection, processing and labeling, preprocessing, feature extraction, feature selection, classification, model evaluation, and finally prediction of new data. Furthermore, several algorithms, namely SVM, CNN, RNN, LSTM, and GRU, were compared. SVM demonstrated its ability to manage high-dimensional data with limited samples, although its capacity to capture temporal dynamics may be constrained. CNN can autonomously learn relevant features from raw data but necessitates substantial amounts of labeled data and can be computationally challenging. RNN captures short-term dependencies in sequential data but may be hindered by the vanishing gradient problem and limited in capturing long-term dependencies. LSTM can address the vanishing gradient problem and capture long-term dependencies, but it can also be computationally burdensome. GRU, similar to LSTM but with fewer parameters, can be quicker to train, making it beneficial in scenarios where labeled data is limited or sequence-to-sequence learning is required.

These algorithms were tested alongside some traditional machine learning algorithms. Each classifier model was trained on (X and Y) data, predictions for the test data were made, and the classification was printed. This included Accuracy, Recall, F1 score, and support for each, separately. Additionally, the confusion matrix was calculated and depicted using the confusion matrix. These were compared with the proposed model specifically designed for this study, which encompasses the integration of two algorithms (Multi 1D CNN & GRU).

Our custom-constructed model, with its multi-layered architecture, attains noteworthy accuracy levels on both training and testing datasets. When integrating CNN and GRU and training the model, results of 84% accuracy were obtained, exceeding the performance of other classifiers. The model was also trained on LSTM, less efficient results were achieved, with an accuracy of 67% .

The results suggest that our custom neural network model, which integrates convolutional and recurrent layers, exhibits competitive accuracy levels in emotion recognition. Moreover, it surpasses traditional machine learning classifiers across multiple emotion categories. This underlines the potential of advanced neural network architectures in augmenting emotion recognition capabilities, which could have significant implications for applications such as human-computer interaction and mental health monitoring.

As the field of emotion recognition advances, the incorporation of advanced neural network models harbours substantial promise for real-world applications, ultimately contributing to the development of more emotionally intelligent AI systems.

5.2 FUTURE WORK

In this research, we proposed an innovative architecture for emotion recognition in EEG signals by synergizing multiple 1D CNN layers with a GRU layer. This architecture aims to exploit the strengths of both CNNs and GRUs to effectively capture and model the complex temporal dynamics inherent in EEG data.

Future works can explore and incorporate alternative structures. For instance, a combination of LSTM and CNN or RNN could be utilized.

The dataset employed in this study was captured, processed, and input via a MindWave portable device, lending strength to the study by relying on a self-constructed dataset rather than a pre-existing, published one. However, this feature also introduces drawbacks, including the cost of EEG signal capture devices and some devices' limitations in capturing EEG signals. These limitations include a restricted number of columns (samples) such as 'Attention', 'Meditation', 'delta', 'theta', 'low-alpha', 'high-alpha', 'low-beta', 'high-beta', 'low-gamma', and 'mid-gamma'. This could negatively impact classification results and accuracy. Pre-existing datasets, with their larger sample sizes, might provide superior model training results when used.

Furthermore, the enhancement of results is influenced by several factors, including the number of filters for feature extraction, the number of layers, and the number of time periods. The accuracy of results could also be improved by reducing the number of ratings or emotional features. For instance, in our study, emotions were divided into five traits (sad, angry, happy, calm, and neutral). These could be replaced with fewer attributes such as negative condition, normal condition, and positive condition. This would increase the relative difference between the values of the data captured through the supervised technique, potentially enhancing model performance.

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