Analysis of Different Frequency Band in EEG Signals for Cognitive Based Specific Emotions.

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Abstract*—In this research, various EEG frequency bands are analyzed to identify cognitive-based specific emotions with the help of DEAP (Dataset for Emotion Analysis using Physiological Signals). The demand for accurate and scalable systems for detecting human emotional states is increasing, particularly for understanding the mental status of individuals who are unable to communicate their emotions, like the one with disabilities or cognitive challenges. EEG signals are great non-invasive method to capture various brainwave patterns which are associated with distinct emotions. Previous studies have demonstrated the potential of EEG in emotion recognition, with the help of different machine learning techniques to achieve promising results. However, challenges remain in accuracy and scalability. Each frequency band are associated with specific cognitive and emotional states, making accurate detection of these bands essential for understanding the neural mechanisms underlying emotions. This study aims to enhance emotion recognition in practical applications and mental health monitoring. Advanced machine learning algorithms including biLSTM, are being utilized to classify emotions based on EEG data, with the goal of improving recognition accuracy.

***Keywords*—EEG, DEAP, Brainwave patterns, biLSTM, frequency bands.**

I. INTRODUCTION

Emotions are essential components of human cognition, influencing decision-making, behavior and overall well-being. Recognizing emotional states is particularly crucial in scenarios where individuals may find it challenging to communicate their feelings, such as those with disabilities or cognitive impairments. Accurate identification of emotional states can provide important insights into mental health in individuals.

Electroencephalography (EEG) has emerged as a powerful tool for studying the neural correlates of emotions due to its capability to monitor the brain's electrical activity in real-time. EEG captures various frequency bands- delta, theta, alpha, beta and gamma. These frequency bands are associated with specific cognitive and emotional states. For instance, Delta waves are associated with deep sleep, unconsciousness and regeneration process, Theta waves linked to relaxation, drowsiness, meditation and light sleep, Alpha waves are associated with relaxed but alert state, Beta waves are associated with active thinking, focus, alertness and cognitive task-like anxiety, stress or excitement and Gamma waves involved in higher cognitive functions like perception and consciousness or heightened awareness. EEG used to trace brain electrical activity with the help of electrodes. There is a standardized system to place EEG electrodes on the scalp for

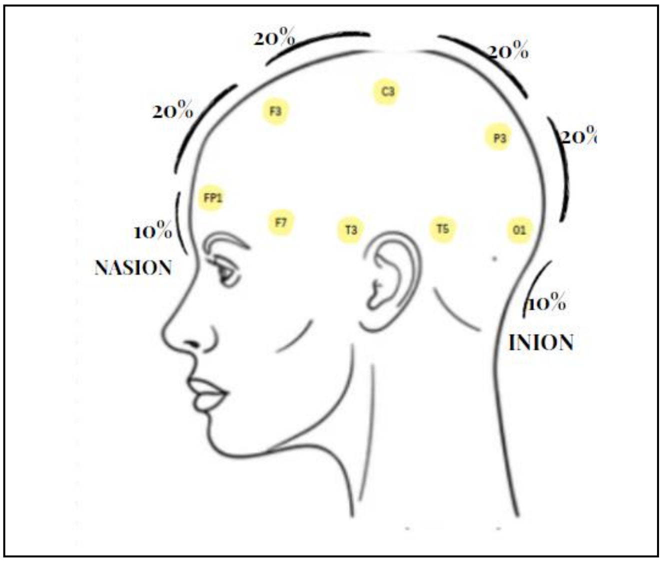

Fig.1. EEG Electrode Placement 10 20 Interval

ensuring the consistent and reliable recordings. This system is basically a 10-20 International system which refers the fact that the electrodes are placed at the intervals of either 10%or 20% of the total distance between specific anatomical landmarks (Nasion and Inion) on the head (shown in Fig. 1). In our brain there are various regions like Frontal(F), Central(C), Temporal(T), Parietal(P) and Occipital (shown in 1.1). The number of electrodes placed varies in different individuals from 16, 32 to 64. Each electrode carries a number with it, odd number indicates the left side of head (like F3, P1), Even numbers indicate the right side of the head (like F4, P2) and electrodes placed along the midline of the scalp are marked with a Z (like Oz, Pz).

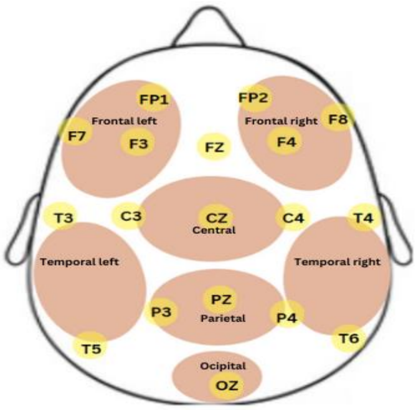

Figure.1.1. Brain Regions

The goal of our research is to enhance the accuracy and efficiency of emotion recognition by analyzing the EEG frequency bands linked to cognitive -based specific emotions with the help of well-known DEAP dataset. By studying distinct brainwave patterns, we aim to understand how these frequencies correspond to emotions such as happiness, sadness and fear, with the ultimate objective of building more accurate system. To structure our emotion analysis, we are going to use Russell's Valence-Arousal Scale, a great accepted model for categorizing emotions which include Valence and Arousal. Valence depicts how positive or negative a model is and Arousal depicts the intensity of an emotion. By mapping emotions into valence and arousal we can interpret EEG patterns linked to emotional states with greater precision like excitement (high arousal and positive valence) and sadness (low arousal, negative valence). In our research paper we are using machine learning workflow with the focus on leveraging the DEAP dataset which is a well-established resource that provide the EEG recordings and peripheral physiological signals label data. The workflow of our research paper includes data collection, preprocessing, feature extraction, emotion classification using valence-arousal model, validation and accuracy. By incorporating Russell's Valence -Arousal Scale and leveraging the extensive EEG data from the DEAP dataset, this research aims to develop a scalable, high accuracy system for emotion detection. This system has potential applications in brain computer interfaces (BCI), mental health monitoring and emotion- aware technologies.

II. LITERATURE SURVEY

A recent study [1] introduced the ATDD-LSTM model for EEG-based recognition, improving upon traditional hand-crafted feature methods. The deep learning model integrates an Attention-based LSTM to capture spatial features and prioritize EEG channels linked to emotions. In another study [2], the authors proposed an optimized deep CNN for emotion recognition, utilizing a hybrid hunt optimization technique. The approach adjusts CNN hyperparameters and selects informative EEG electrodes based on brain activity, enhancing model performance. This optimized model achieved high accuracy rates of 96.60% and 95.80% across two datasets. This contribution highlights the effectiveness of hybrid optimization in improving emotion detection through deep learning.

If we discuss the different frequency bands and their distinct characteristics, they play a crucial role. Various studies indicate that Delta waves, generally linked to deep sleep and also have been found to have a role in emotion regulation and cognitive function during awake states. Research by Knyazev [3] indicated that delta activity is associated with motivation and emotional arousal. Studies have shown a correlation between high delta wave and emotional states like sadness and calmness. Additionally, delta waves have been found to influence decision -making and self -regulation, highlighting their role in emotional processing. If we discuss about the theta frequency band, they are majorly known for their involvement in memory and learning. A study by Klimesch [4] demonstrated that the theta activity increases during the tasks that demand emotional regulation and cognitive load. Theta band oscillations are essential for linking emotional valence to cognitive processes. For instance, research by Aftanas and Golosheykin [5] observed a arise in the theta activity in subjects experiencing high emotional engagement, suggesting a strong relationship between theta waves and emotion-driven cognitive processing. Regarding the alpha frequency band, it is primarily associated with the relaxation and cognitive rest but also plays a key role in emotional regulation. Studies like those by Coan and Allen [6] have shown that alpha asymmetry, particularly in frontal brain regions, serves as a reliable indicator of emotional states. Specifically, increased right-frontal alpha activity has been linked to negative emotions, while left- frontal alpha corresponds to positive emotional states. This emphasizes the importance of alpha waves in differentiating emotional responses. Beta waves, on the other hand, are linked to alertness, concentration and cognitive functioning, often rising during heightened emotional arousal.

Ray and Cole [7] found that greater beta activity correlates with emotional excitement and anxiety. Beta waves have also been observed during the expression of emotions like happiness and anger, making them crucial for understanding the intensity of emotions and cognitive alertness during emotional experiences. Gamma waves, which operates at the highest frequency, are key to high-level cognitive processing and have a strong connection to emotional responses. Research by Keil et al. [8] found that gamma oscillations are associated with emotional arousal and attention, especially in tasks requiring the integration of sensory and emotional stimuli. Gamma band activity also increase during emotionally intense moments, highlighting its significance in analyzing complex emotional states. Recent studies often combine different frequency bands for a more comprehensive approach to emotion recognition. For example, Murugappan et al. [9] developed an EEG-based emotion recognition system that utilized delta, theta, alpha, beta and gamma bands to improve classification accuracy. Their findings revealed that specific combinations, particularly theta and beta, offers valuable insights into the interplay between cognitive load and emotional responses.

Koelstra et al. [10] introduced the DEAP dataset, a widely used resource of emotion analysis through physiological signals like EEG and peripheral signals. The dataset includes recordings from 32 participants watching 40 one- minute music videos. EEG signals were recorded from 32 electrode, with emotions rated using valence, arousal, dominance and liking scales. The DEAP dataset has become a benchmark for emotion recognition models and is commonly used to test algorithms aimed at emotion analysis. Zhang et al. [11] applied a CNN-based framework for attention recognition using DEAP dataset, focusing on EEG signal analysis. While the study primarily examined attention, it demonstrated the potential of deep learning models to identify cognitive states from EEG data, with the possibility of extending this approach to emotion recognition tasks.

III. METHADOLOGIES

In order to identify and categorize various emotions, the approaches used in our study paper concentrate on examining various frequency bands in EEG signals. We are aiming to analyse these signals and identify the emotions using Russell's valence and arousal with the aid of the comprehensive and well-known DEAP dataset, which contains a variety of physiological signal data. To categorize and predict emotions depending on various states, we will use both machine learning and deep learning approaches in our case. These techniques include machine learning classifiers and biLSTM.

The Methodologies that we employ in our work include data preprocessing, feature extraction, classification, prediction and model evaluation, shown below in Fig.2.

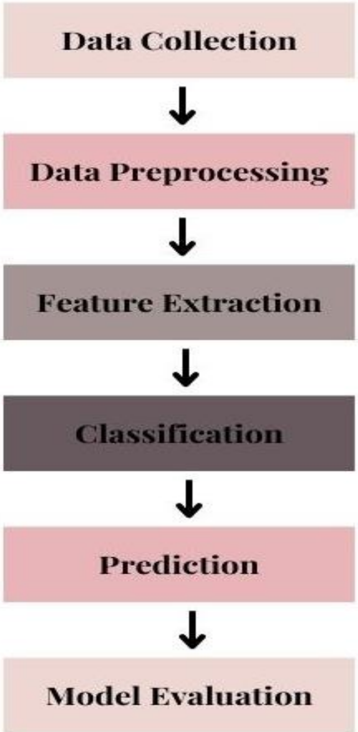

Fig.2. Proposed Model

In order to execute our model first we have to utilise DEAP dataset for data preprocessing, which is the initial step where we use to prepare raw EEG data for analysis and classification, the raw EEG data have their EEG signals and labelled ratings. The data used to get reshaped and organized into NumPy arrays also in sideline artifacts removal and filtering happen for initiating efficient processing. Moving forward as a part of feature extraction the primary goal is to extract the band power of each frequency band which represents the strength of a particular frequency range within a signal. After extracting the pertinent features, we will proceed to the next step, where we grouped our features into four emotional categories which are HAHV, LAHV, HALV, LALV .These four categories are decided based on the ratings of valence and arousal median splits. In order to classify emotions, we use various machine learning classifiers like SVM, KNN and MLP where the classifiers are trained on a portion of data which is training dataset to analyse the pattern and relationship between EEG features(band power) and labels. After analysing the pattern, it shows that KNN works great for valence data(62%) and MLP works great for Arousal data(68%) due to its temporal dynamics. For prediction BiLSTM model works well due to their advance techniques like processing data from both directions (forward and backward).

A. DEAP Dataset

DEAP stands for “Dataset for Emotion Analysis using Physiological Signals”[12]. It’s a well-known high-quality dataset used for studying various human emotional states based on EEG and various peripheral physiological signals. . EEG is one type of data in DEAP. which has 32 participants(16 male, 16 female), ranging in age from 19 to 37. Every participant viewed a music video designed to make them feel different kinds of emotions. These responses are gathered using electrodes(32 channels) positioned on the head in various areas (such as the frontal and occipital regions) in accordance with the 10–20 interval scheme. A sample of the response signals is taken at 128 Hz. We will now extract frequency bands for each trial by using bandpass filters. Bands of frequencies such as deta, gamma, theta, alpha, and beta , shown in Table.2. In our research we have used a portion of DEAP dataset, where we have used 5 subjects. The dimension of our data is shown below in Table.1.

TABLE 1. DATA DIMENSION

LABEL	ENTIRE DATASET
(200, 4)	(200, 40, 8064)

TABLE 2. FREQUENCY BANDS RANGE

S.no	Frequency Band in EEG	Frequency Range
1	Delta	0.5-4 Hz
2	Theta	4-8 Hz
3	Alpha	8-12 Hz
4	Beta	12-30 Hz
5	Gamma	30-60 Hz

B. BiLSTM

An enhanced form of LSTM, bidirectional long short term memory (BiLSTM) network which works on sequential data like LSTM, but it works in both directions: forward and backward which help them to record both past and future dependencies.[13] BiLSTM network is formed using two parallel LSTM layers(forward LSTM and backward LSTM) shown in Fig.3. Forward LSTM processes the input sequence from the beginning to the end and the backward LSTM processes it in reverse manner. At last, the output from these two layers get concatenated at each timestep giving a more comprehensive representation of the input by taking the whole context into account.BiLSTM foundation is the LSTM network, which was created to work on sequential data by solving vanishing gradient problem which traditional RNNs experience.[14] The LSTM supports the network to learn and sustain long term relationships in sequences via the addition of memory cell and three gates: forget, input and output gates which controls the information flow .The forget gate controls which memory(data) need to be discard from previous memory(cell state), the input gate decides which information to add and output gate decides which data must be passed to next timestep,shown in Fig.4.

While LSTMs are good at learning correlations over time, they can only learn in one direction. This may limit their capacity to utilize the context to its fullest, especially during activities where relevant insights are obtained from future knowledge. By combining the benefits of forward and backward LSTMs, BiLSTM overcome this constraint by processing the sequence in both directions.

The mathematical intuition behind BiLSTM is shown below.

In Forward Pass**,** let X be an input sequence $X = [x_1, x_2, x_3, x_4 \dots x_t]$,the input sequence is processed by the forward LSTM from t = 1to t = T. At each time step t.

Below $f_t^{forward}$ represents forget gate, $i_t^{forward}$ represents input gate, $O_t^{forward}$ represents output gate, $\acute{C}_t^{forward}$ represents candidate memory(it stores potential important information which can be added to cell state), $C_t^{forward}$ represents cell state(long-term context) and $h_t^{forward}$ represent hidden state(short-term context) in forward LSTM.

$$f_t^{forward} = \sigma(W_t^{forward} \cdot [h_{t-1}^{forward}, x_t] + b_f)$$

$$i_t^{forward} = \sigma(W_i^{forward} \cdot [h_{t-1}^{forward}, x_t] + b_i)$$

$$\acute{C}_t^{forward} = \sigma(W_C^{forward} \cdot [h_{t-1}^{forward}, x_t] + b_C)$$

$$C_t^{forward} = f_t^{forward} \cdot C_{t-1}^{forward} + i_t^{forward} \cdot \acute{C}_t^{forward}$$

$$O_t^{forward} = \sigma(W_O^{forward} \cdot [h_{t-1}^{forward}, x_t] + b_O)$$

$$h_t^{forward} = O_t^{forward} \cdot tanh(C_t^{forward})$$

In Backward Pass**,** the input sequence is processed in reverse order by the backward LSTM.

Below $f_t^{backward}$ represents forget gate, $i_t^{backward}$represents input gate, $O_t^{backward}$ represents output gate, $\acute{C}_t^{backward}$ represents candidate memory(it stores potential important information which can be added to cell state), $C_t^{backward}$ represents cell state(long-term context) and $h_t^{backward}$ represent hidden state(short-term context) in backward LSTM.

$$f_t^{backward} = \sigma(W_t^{backward} \cdot [h_{t-1}^{backward}, x_t] + b_f)$$

$$i_t^{backward} = \sigma(W_i^{backward} \cdot [h_{t-1}^{backward}, x_t] + b_i)$$

$$\acute{C}_t^{backward} = \sigma(W_C^{backward} \cdot [h_{t-1}^{backward}, x_t] + b_C)$$

$$C_t^{backward} = f_t^{backward} \cdot C_{t-1}^{backward} + i_t^{backward} \cdot \acute{C}_t^{backward}$$

$$O_t^{backward} = \sigma(W_O^{backward} \cdot [h_{t-1}^{backward}, x_t] + b_O)$$

$$h_t^{backward} = O_t^{backward} \cdot tanh(C_t^{backward})$$

At last, while predicting the result of BiLSTM the output from the forward and backward LSTM are concatenated.

$$h_t^{BiLSTM} = concatenate(h_t^{forward}, h_t^{backward})$$

Above $h_t^{forward}$ represents the output which we get from forward LSTM, $h_t^{backward}$ represents the output which we get from backward LSTM and h_t^{BiLSTM} represents what we get at the end as the result by concatenating both forward and backward LSTM output.

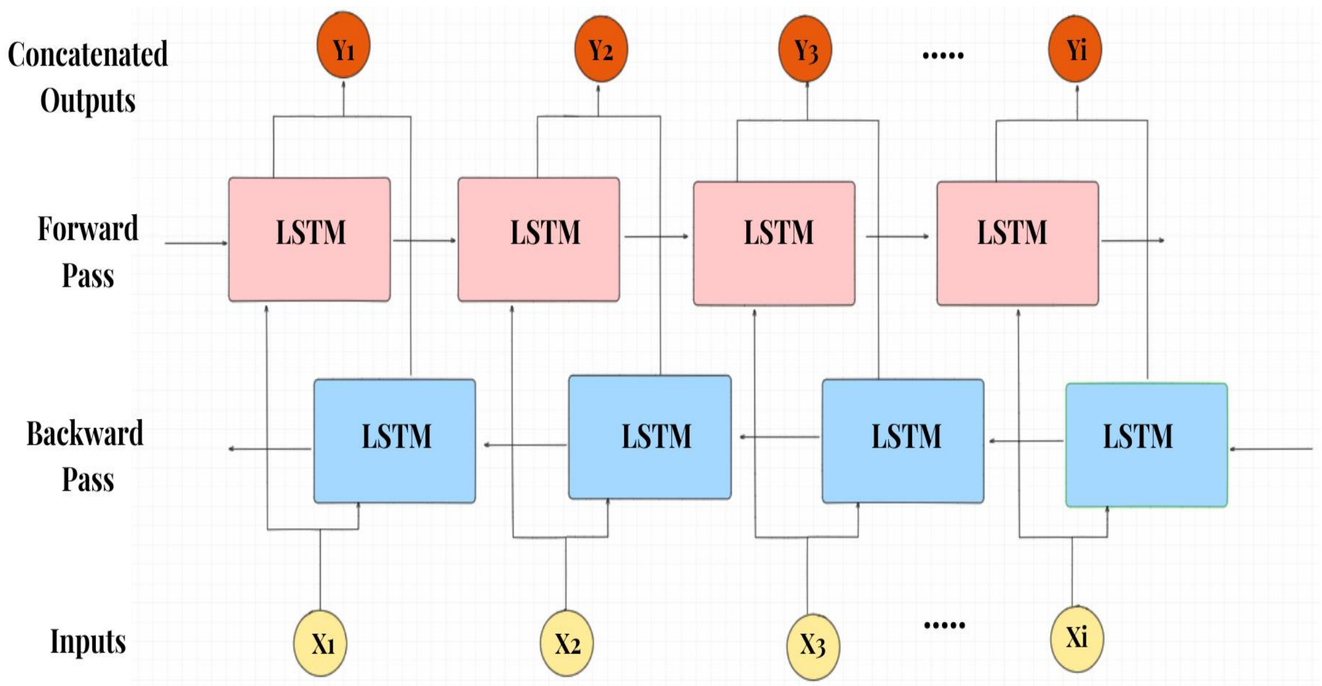

Fig.3. Bidirectional Long-Short Term Memory Model (BiLSTM)

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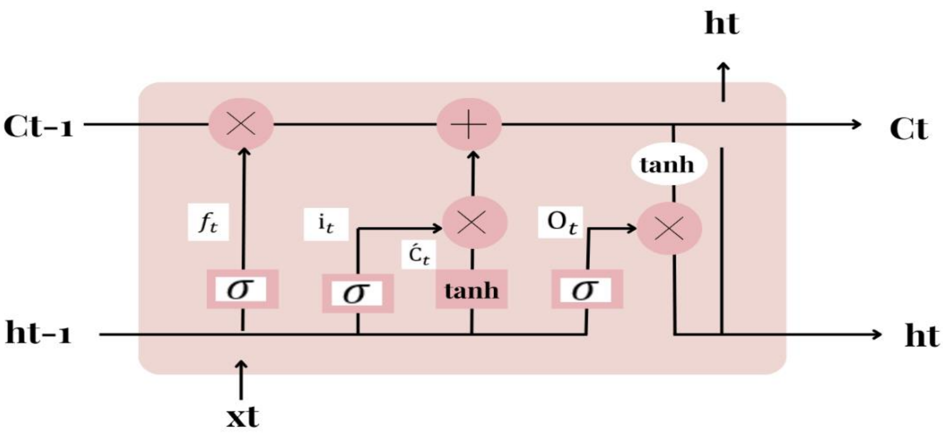

Fig.4. Long Short-Term Memory Model (LSTM)

IV. RESULTS

The deployed models' strengths in EEG-based emotion recognition are highlighted by the performance evaluation. Using it ease of use and ability to detect localized patterns, the K-Nearest Neighbours(KNN) method performed exceptionally well in valence classification because of its capacity to learn intricate non-linear relationships, the Multi-Layer Perceptron(MLP) performed better than other models in the classification of arousal levels. Furthermore, the Bidirectional Long Short-Term Memory(BiLSTM) model demonstrated skills by capturing temporal relationships in EEG data, achieving a training accuracy of 92% and a testing accuracy of 85%, shown in Fig.5 and Fig.6. This analysis highlights the complimentary characteristics of these models, where KNN offers interpretability, MLP manages non-linear data successfully and BiLSTM succeeds in sequential pattern learning.

The comparative effectiveness of three approaches for EEG-based emotion recognition is shown below in Table.3. Our approach demonstrated good generalization with 92% training and 85% testing accuracy. The training accuracy in Huang et al.'s [15] paper is approximately 85% whereas the testing accuracy is around 78%. The intricacy of feature extraction and difficulties with inter-subject variability are the reason for their study's poorer accuracy. The training accuracy of Zhu et al.'s study[16] is approximately 83% whereas the testing accuracy is around 77%. Once more, these numbers are lower than ours, most likely as a result of variations in the model architecture and comparable difficulties in feature extraction. While both trials show encouraging outcomes overall, their performance is slightly less favourable than ours. Although the stated accuracy suggest that additional feature selection and model modification may be necessary to attain higher performance, especially in testing phases, the usage of CNN, Bi-LSTM and attention mechanisms in their investigations offers valuable insights. Our method's better testing accuracy indicates that the feature extraction techniques and network architectures chosen may have been more resilient when processing the EEG signals for emotion recognition.

TABLE 3. RESULTS COMPARISON

Methodology	Training Accuracy	Testing Accuracy
Our Result	92%	85%
Huang et al. (2023)	85%	78%
Zhu et al. (2024)	83%	77%

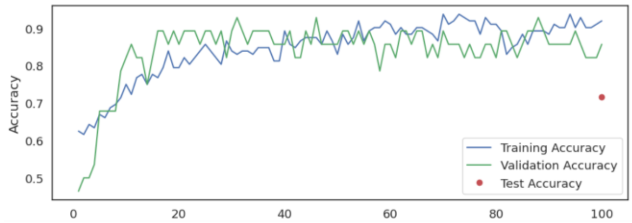

Fig.5. Training, Validation and Test Accuracy

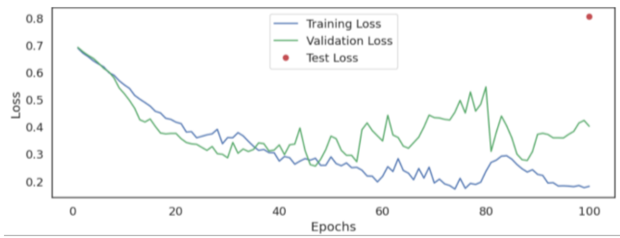

Fig.6. Training, Validation and Test Loss

V. CONCLUSION

In this work, we implement a BiLSTM (Bidirectional Long Short-Term Memory) model to examine EEG-based emotion recognition. Our model showed a great capacity to generalize across unseen data, achieving 92% accuracy on the training dataset and 85% accuracy on the testing dataset. Several current approaches, including those Huang et al. (2023) and Zhu et al. (2024), which stated lower testing accuracy, perform worse than these results. The benefit of using sequential data and capturing temporal connections in EEG signals for emotion recognition is demonstrated by the success of our BiLSTM model. Despite these encouraging findings, issues like subject- specific variability and the intricacy of interpreting EEG signals still exist. Better performance may be attained with further feature extraction and model optimization techniques, which would make our method a strong contender for practical use in emotion identification systems.

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