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PROJECT PHASE - I REPORT

on

"Deep Learning Based Emotion Analysis from EEG Data"

Submitted by

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Under the Guidance of

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COLLEGE OF ENGINEERING & MANAGEMENT
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CERTIFICATE

This is to certify that the **Project Work Phase - I** entitled **"Deep Learning Based Emotion Analysis from EEG Data"** has been carried out by **Deepthi Kashyap M K (4SF22EC027), Hemanath Kumar H N (4SF22EC042), Mahesh (4SF22EC056), Sneha (4SF22EC107)**, the bonafide students of Sahyadri College of Engineering & Management, in partial fulfillment of the requirements for the VI semester **Project Work Phase - I (EC622P6E)** of **Bachelor of Engineering in Electronics and Communication** of Visvesvaraya Technological University, Belagavi during the year 2024-25. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the Report deposited in the Departmental library.

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DECLARATION

We hereby declare that the entire work embodied in this Project Report titled **"Deep Learning Based Emotion Analysis from EEG Data"** has been carried out by us at Sahyadri College of Engineering and Management, Mangaluru under the supervision of **Mrs.Roopashree** as the part of the VI semester **Project Work Phase - I (EC622P6E)** of **Bachelor of Engineering** in **Electronics and Communication Engineering**.This report has not been submitted to this or any other University.

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Abstract

Emotion inference from electroencephalogram (EEG) signals is a new field of artificial intelligence with numerous applications in brain computer interfaces, real-time human machine interfaces, and mental state measurement.EEG signals transmit high-temporal and frequency-domain information of emotion states. In this article, a new approach of deep learning with assistance from long short-term memory (LSTM) networks for emotion classification of EEG recordings—anger, happiness, sadness, and fear—is introduced. Preprocessing pipeline includes Fast Fourier Transform (FFT) for frequency feature extraction, normalization, and reshaping into sequence format to maintain temporal dependences. LSTM-based model includes stacked layers of LSTMs, dense fully connected layers, and dropout layers to avoid overfitting. It was trained on emotion labels encoded with one-hot and tested on a different test set.

Recent trends reflect that the integration of CNN and LSTM architecture improves classification by learning spatial and temporal features of EEG signals [1]. Furthermore, methods like graph convolutional LSTM networks and attention have improved accuracy by modeling EEG signal inter-channel correlations [2]. The proposed model was shown to improve the accuracy of classification in depicting the capability of the model to learn complex sequential patterns in EEG data. This project is concerned with the potential for the creation of real-time, non-invasive affect sensing systems to facilitate affective computing research, self-monitoring of mental states, and adaptive user-adaptive systems.

Acknowledgement

It is with great satisfaction and euphoria that we are submitting the Project Phase I Report on **"Deep Learning Based Emotion Analysis from EEG Data"**. We have completed it as a part of the VI semester **Project Work Phase - I (EC622P6E)** of **Bachelor of Engineering** in **Electronics and Communication)** of Visvesvaraya Technological University, Belagavi.

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Table of Contents

List of Figures

List of Tables

Abbreviations

Abbreviation	Full Form
ANN	Artificial Neural Network
AUC	Area Under Curve
BCI	Brain-Computer Interface
CNN	Convolutional Neural Network
DWT	Discrete Wavelet Transform
DEAP	Dataset for Emotion Analysis using Physiological signals
EEG	Electroencephalography / Electroencephalogram
EMG	Electromyography
ERP	Event-Related Potential
FER	Facial Expression Recognition
FFT	Fast Fourier Transform
FPS	Frames Per Second
HOG	Histogram of Oriented Gradients
ICA	Independent Component Analysis
k-NN	k-Nearest Neighbors
LBP	Local Binary Pattern
LSTM	Long Short Term Memory
MAE	Mean Absolute Error
MFCC	Mel Frequency Cepstral Coefficients
MLP	Multi-Layer Perceptron
P300	Positive peak at 300 ms (an ERP component)
PCA	Principal Component Analysis
PSD	Power Spectral Density
ReLU	Rectified Linear Unit
RGB	Red Green Blue
RMSE	Root Mean Square Error
ROI	Region of Interest
SAM	Self-Assessment Manikin
SEED	SJTU Emotion EEG Dataset
STFT	Short-Time Fourier Transform
SVM	Support Vector Machine

Chapter 1

Introduction

1.1 Background of the Study

Affective computing is an important and emerging branch of artificial intelligence (AI) with enormous potential for usage in mental health monitoring, human-computer interaction, adaptability, and affective computing. Emotions are central to human behavior and influence decision-making, communication, learning, and perception. Accurate identification of emotional states can enable more intelligent and more sympathetic AI systems that will respond accordingly to the needs of the users [3]. Electroencephalography (EEG) provides a viable approach to emotion quantification in terms of direct recording of electrical activity from the brain via scalp electrodes. EEG signals carry informative information regarding different states of emotions such as happiness, sadness, anger, and fear. EEG signals identify neural oscillations and patterns of different brain activities, and thus EEG is a source of rich information for emotion classification. We examine, in this paper, the use of Long Short-Term Memory (LSTM) networks to detect emotional states from EEG signals. LSTM networks are a type of recurrent neural network that is tuned for learning temporal patterns in time-series data. Their ability to retain information over long sequences positions them as excellent candidates for modeling the time evolution of EEG recordings [4]. The EEG signals are preprocessed first with the Fast Fourier Transform (FFT) to convert them from the time domain to the frequency domain. This is apparent in power assignment over different frequency bands such as delta, theta, alpha, beta, and gamma, which have been said to be associated with affective and cognitive processing. These frequency-domain features are normalized and reshaped in order to build the input to the LSTM model.The LSTM network is learned to recognize emotional states from such frequency characteristics. Learning intricate temporal patterns in the EEG series, the model differentiates emotions like anger, happiness, sadness, and fear. The results indicate the suitability of employing LSTM architectures for brain signal decoding and emotion recognition [5]. This strategy centers on the possibilities of creating real-time, brain-based emotion recognition systems. These can be integrated into a variety of applications such as stress monitoring, adaptive learning systems, personalized user interfaces, and emotional feedback systems for virtual reality. Due to the ready availability and ease of using EEG hardware, the implementation of LSTM-based emotion recognition solutions is likely to be the driving force behind emotionally intelligent technology development.

1.2 Organization of Thesis

This report is organized into the following chapters,

Chapter 1: Introduction, this presents the project topic, including Background of the study, Problem statement, Objective, Scope of the work, and Motivation of the project.

Chapter 2: Literature Survey, elaborates appropriate literature related to topic is analysed. It emphasizes theories, model, and previous research that form a framework for our study, and determines the gaps identified.

Chapter 3: Methodology, describes the methodology used to build a project. This includes data collection, data preprocessing, feature extraction, model training, and model evaluation.

Chapter 4: System Design, contains classification models, Contrast used for designing a project.

Chapter 5: Results and Discussions, the result of this project is presented in this chapter. This chapter consists of model performance evaluation, comparison with other models, insights and future work.

Chapter 6: Conclusions summarizes the project, key findings, and future work.

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Chapter 2

Literature Review

The literature review is essential for understanding current research on mind-controlled gaming interfaces. It provides insights into approaches, difficulties, and breakthroughs while highlighting critical gaps in existing research. This chapter, which is crucial to our report, presents an overview of existing studies and frameworks linked to AI-Driven Home Layouts, leading our efforts to fill research gaps and promote innovation in this sector.

Iyer et al. [1] propose an ensemble architecture that integrates Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to detect emotions from EEG signals. Their approach successfully detects spatial and temporal features in brain activities, which improves the performance of the system to classify the emotion state. The research highlights the capacity of deep learning models to extract useful features from EEG recordings to support affective computing applications.

Feng et al. [2] propose an ensemble model that integrates Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to recognize emotions from EEG signals. Their approach successfully captures spatial as well as temporal characteristics of brain activity, and it improves the system's performance for classifying emotional states. Their research highlights the potential of deep learning models to recognize useful features from EEG to facilitate affective computing technologies.

Soleymani et al. [3] examine a persistent emotion recognition system that integrates EEG signals with facial expression. By exploiting the merits of both physiological and visual modalities, the research seeks to enhance the reliability of tracking emotions in the long term. The article illustrates the strength of multimodal approaches to understand the nuance of human emotional reactions, particularly where arousal and valence are involved.

Nath et al. [4] offer a practical approach for affect recognition using EEG with an LSTM network. Their method is interested in acquiring temporal dependency of EEG signals for classifying affective states accurately. The paper demonstrates that LSTM networks are quite capable of handling the sequential nature of EEG data and hence provide an efficient approach for real-time affective computing.

Chen et al. [5] present a multimodal dataset for emotion recognition that includes audio, video, EEG, and EMG signals. Along with the dataset, they introduce baseline models to contrast the efficiency of different modalities and compositions. The paper offers handy resources and benchmarks for those interested researchers who aim to explore emotion recognition from diverse physiological and behavioral streams of data.

KoeKoelstra et al. [6] possess physiological signals like EEG for affective analysis. It offers affective labels of arousal and valence, hence simplifying emotion recognition algorithms. The paper underlines the necessity of physiological signals and the motivation behind research in multimodal emotion recognition approaches.

Hassouneh et al. [7] constructed a real-time affective emotion recognition system from EEG signals and facial expressions. With deep neural networks and machine learning algorithm, the system will hopefully achieve real-time emotion classification. The paper states the use of multiple modalities of signal as one of the strategies that can be employed to enhance accuracy and responsiveness in emotion recognition.

Soroush et al. [8] provided an overview of the recognition of emotion through EEG, introducing several methods of EEG signal analysis for emotional state detection. The paper makes reference to preprocessing of the signal, feature extraction, and classification algorithms. It introduces challenges and success in EEG-based emotion recognition, hinting at greater accuracy potential.

Huang et al. [9] carried out an experiment of utilizing the combination of EEG signals and facial expressions as a multimodal modality of emotion recognition. It is an investigation into the use of multimodal signals in attempting to increase the accuracy of emotion detection systems in their outputs. A new computational facial and EEG data fusion approach was proposed in the paper for improving the reliability of emotion recognition.

Chao et al. [10] employed Capsule Networks (CapsNet) to identify emotions from multiband EEG signals. CapsNet is said to improve the classification capability over the traditional approaches by learning high-level relations from EEG signals. The paper shows the feasibility of high-level neural network architecture towards enhancing the accuracy of emotion recognition from EEG.

Li et al. [11] also presented a tutorial and overview of EEG-based emotion recognition with challenges and approaches and advancements made. The paper presents different emotion detection methods using EEG signals with focus on signal preprocessing, feature extraction, and machine learning techniques.

Oude Bos [12] conducted EEG-based affect recognition with the focus on the effect of visual and auditory stimulation on it. The article demonstrates how emotional response varies due to sensory input difference while recording using EEG, which represents the neural correlate of emotion processing.

Dadebayev et al. [13] delineated commercial EEG equipment and machine learning methodologies of emotion recognition. The paper outlines some of the drawbacks and advantages of several EEG-based systems, a description of present commercial technologies, and potential applications in emotion recognition as well as possible machine learning methodologies.

Ismail et al. [14] presented a paper on human emotion recognition with EEG signals, exploring the utilization of brain waves for emotional categorization. Methods and algorithms that are used in signal processing in emotion recognition are described in the paper with descriptive information for EEG-based emotion recognition systems.

Wei et al. [15] developed a wearable real-time emotion recognition headband using EEG measurement. The system offers real-time emotion monitoring using EEG for emotional state detection. This demonstrates the effectiveness of wearable technology in emotion recognition and its use in real-time.

Roshdy et al. [16] introduced EEG emotion recognition development under the theme of multi-modal database incorporation usage. The paper addresses how other data sources are utilized in integrating to maximize accuracy on emotion identification as part of very important work of developing successful emotion recognition systems.

Nataraj et al. [17] compared emotion recognition using EEG with the DEAP and

SEED-IV databases, SVM classification. Their paper provides the performance of SVM for emotion classification from EEG, and the implications of using conventional machine learning methods to emotion recognition.

Zamanian et al. [18] introduced a new feature extraction method to enable emotion detection using EEG signals. The paper suggests a new direction in the extraction of useful features from EEG signals, enhancing the efficiency of emotion identification systems and pushing the frontiers of EEG-based emotion recognition.

Ul Hassan et al. [19] proposed an end-to-end machine learning approach for effective emotion recognition through EEG signals. In this work, the machine learning models and their application in EEG recordings are compared and offer a complete study of the top-performing techniques of emotion classification.

Pan et al. [20] suggested a multimodal emotion recognition system by integrating facial expression, speech, and EEG signals. The study reveals the effectiveness of the multimodal approach towards improved accuracy of emotion recognition, and it shows the ability of multimodal systems to recognize complex human emotions.

Table 2.1: Summary of the Literature Survey

Reference	**Proposed Method**	**Dataset Used**	**Results and Discussion**
Iyer et al. [1]	Combines CNN for spatial feature extraction and LSTM for temporal dynamics in EEG data	SEED, DEAP	Achieved 97.16% accuracy on SEED and demonstrated superior performance over standalone CNN/LSTM models on DEAP.

Reference	Proposed Method	Dataset Used	Results and Discussion
Feng et al. [2]	Applies spatial–temporal graph convolutional network with LSTM and attention to model EEG signal dependencies	DEAP, SEED, SEED-IV	Achieved 95.52 % accuracy across benchmark datasets, demonstrating an absolute improvement over prior state-of-the-art methods.
Soleymani et al. [3]	Integrates EEG features with facial expression analysis for continuous emotion tracking	EEG and facial expression data	Demonstrated that combining modalities improved emotion recognition performance.
Nath et al. [4]	Employs LSTM to capture long-term dependencies in EEG signal sequences	DEAP	Achieved 94.69 % accuracy for valence recognition and 93.13 % for arousal recognition on the DEAP dataset, maintaining computational efficiency.
Chen et al. [5]	Introduced a rich multimodal dataset and evaluated baseline models across audio, video, EEG, and EMG signals	PME4 (11 subjects, 6 basic emotions + neutral)	Multimodal fusion outperformed all unimodal baselines.
Koelstra et al. [6]	EEG-based emotion recognition	DEAP	Established a benchmark EEG dataset for emotion recognition.

Reference	Proposed Method	Dataset Used	Results and Discussion
Hassouneh et al. [7]	Real-time emotion recognition using facial expressions and EEG	Real-time data	Improved recognition accuracy via multimodal fusion.
Soroush et al. [8]	Preprocessing, feature extraction, and classification of EEG	Various datasets	Emphasized improvements through optimized signal processing.
Huang et al. [9]	Fusion of facial expressions and EEG	Custom dataset	Multimodal fusion improved classification accuracy.
Chao et al. [10]	Emotion recognition using CapsNet on EEG	Multiband EEG data	CapsNet outperformed CNNs in modeling EEG data.
Li et al. [11]	EEG emotion recognition tutorial and review	Multiple datasets	Summarized challenges and suggested evaluation protocols.
Oude Bos [12]	Visual/auditory impact on EEG emotion response	Proprietary dataset	Demonstrated EEG sensitivity to multimedia stimuli.
Dadebayev et al. [13]	Review of commercial EEG devices and ML	Commercial datasets	Compared device capabilities and algorithm effectiveness.
Ismail et al. [14]	Emotion detection via brain waves	EEG recordings	Validated EEG-based detection with statistical analysis.

Reference	Proposed Method	Dataset Used	Results and Discussion
Wei et al. [15]	Wearable real-time EEG system	EEG from wearable	Built real-time headband for live emotion tracking.
Roshdy et al. [16]	Multimodal database fusion for emotion recognition	Combined datasets	Fusion of modalities enhanced recognition performance.
Kumar and Nataraj [17]	SVM classification with DEAP and SEED-IV	DEAP, SEED-IV	SVM showed reliable cross-dataset performance.
Zamanian and Farsi [18]	New EEG feature extraction method	EEG signals	Improved accuracy via enhanced feature extraction.
Ul Hassan et al. [19]	End-to-end ML approach for EEG signals	EEG datasets	Proposed a robust ML pipeline with high accuracy.
Pan et al. [20]	Fusion of facial, speech, and EEG modalities	Multimodal dataset	Tri-modal fusion significantly outperformed unimodal systems.

2.1 Gaps Identified

Despite numerous research studies in the area of emotion recognition via EEG signals, certain vital challenges are yet to be solved. The models are unable to perform suitably across people due to the fact that the brain signal patterns of everybody differ. They also cannot function real-time because existing devices take time and require high-spec machines. There are effective but deep-learning methods such as LSTM and CNN require a great deal of data and tend to be difficult to interpret. Blending EEG with other signals such as facial expressions is still not commonly used in everyday life. Furthermore, there is no standard procedure for cleaning and preparing EEG data across studies.

Chapter 3

PROBLEM STATEMENT AND OBJECTIVES

3.1 Problem Statement

Emotion recognition based on EEG signals has gained prominence as a subject of research over the past few years with the potential of its use in mental health therapy, affective computing, and human-computer interaction. Since EEG signals are more objective and direct representations of brain activity compared to external signals like facial expressions or speech, they can be an effective tool for identifying the emotion state. Electrical signals, recorded by sensors placed on scalp, reflecting underlying cognition and affective processes. Yet, EEG data are typically high-dimensional, noisy, and time-varying, and the most significant challenge for emotion classification. In addition, inter-individual and inter-stimulus differences in brain wave patterns make it impossible to build a generalized emotion recognition model. In an attempt to overcome these hurdles, the current study is aimed at utilizing Convolutional Neural Networks (CNNs), a deep neural technique that is often described as extracting relevant bounces features from raw data. CNNs were discovered to be superior at image and signal processing tasks by utilizing the extraction of local spatial patterns and dependencies. In EEG-based emotion recognition application, CNNs can learn the spatial correlations between various electrodes locations and frequency bands and effectively differentiate emotional states without feature extraction. The aim of this project is to develop a CNN-based model that can identify the extracts affective states like happiness, sadness, fear, and anger from preprocessed EEG signals. Application of frequency-domain transformation methods, such as Fast Fourier Transform (FFT), also improves feature representation for CNN input.

The final aim is to apply a robust real-time emotion detection system that can be incorporated in wearable EEG devices, with promising applications in stress monitoring, mental health evaluation, and adaptive interfaces. This system will also examine the possibility of integrating EEG emotional analysis into intelligent environments, delivering real-time emotional feedback to enhance user well-being and individualized experience. The project strives, by this method, to close the gap between neuroscience and AI towards emotionally intelligent systems that react and learn correspondingly with human emotions.

3.2 Objectives

- To develop a deep learning-based model using LSTM networks for accurate emotion recognition from EEG signals.
- To preprocess and structure EEG data using FFT for effective learning of temporal emotional patterns.
- To evaluate the model's performance and explore its potential in real-time applications like mental health monitoring and human-computer interaction.

3.3 Scope of the Work

- **Develop real-time emotion recognition based on real-time EEG signal processing:** Real-timeprocessing will be able to allow real-time emotional state monitoring. This is vital for real-time response-based systems, i.e., stress control or adaptive systems.
- **Use the system together with wearable EEG headsets in order to use it conveniently and move around freely:**Utilize wearable EEG headsets for detecting emotions convenient and mobile keeps accessibility and convenience within easier reach so one can track emotions on-the-move.
- **Apply the model in real-world applications like stress sensing and tracking mental wellbeing:** Real-time emotional monitoring can be greatly

beneficial for gaining insight into mental wellbeing, assisting in depression or anxiety. Log incessantly in order to allow personal stress and emotion control.

- **Combine EEG signals with other modalities such as facial expression or voice for better accuracy:** Combining EEG signals with other modalities such as facial expression or voice enhances detection accuracy. A multimodal approach of this type allows better and more richer interpretation of the emotional state of a person.

- **Enhance the model to execute quickly and with minimal deployment on edge devices:** Model enhancement for edge devices reduces processing time and latency. It enables emotional detection to potentially execute successfully on mobile devices like smartphones and IoT devices without going to the cloud.

3.4 Motivation of the Report

The motivation for this project is the growing significance of emotion recognition through EEG signals for real-time mental state monitoring, brain-computer interfaces, and real-time human-computer interaction. The traditional methods, although well performing under some contexts, degrade when there are intricate temporal patterns of EEG signals. Deep models, i.e., Long Short-Term Memory (LSTM) networks, provide better results and coping sequential data. In this research, the detection performance of LSTM's emotion recognition for EEG signals, i.e., real-time detection performance, will be investigated. The goal is to enhance applications such as monitoring mental wellbeing, adaptive systems, and personalized feedback mechanisms. Having a performance and accuracy goal focus, this research will create emotion-aware technologies and human-computer interaction and open up new prospects for real-time emotion recognition in healthcare and consumer environments.

Chapter 4

METHODOLOGY

4.1 Block Diagram

Emotion recognition based on EEG signals has attracted a lot of interest because of the potential to recognize human affective states from brain activity. Deep learning models, especially those optimized for sequential data such as LSTM networks, are being used more and more to analyze EEG signals because they can learn temporal dependencies and fine-grained patterns over time. The below block diagram depicts a well-organized methodology for developing an emotion recognition system based on EEG through an LSTM model. This method guarantees proper preprocessing of the raw EEG data, organization, and input into an excellently optimized deep learning model to obtain correct emotion classification.

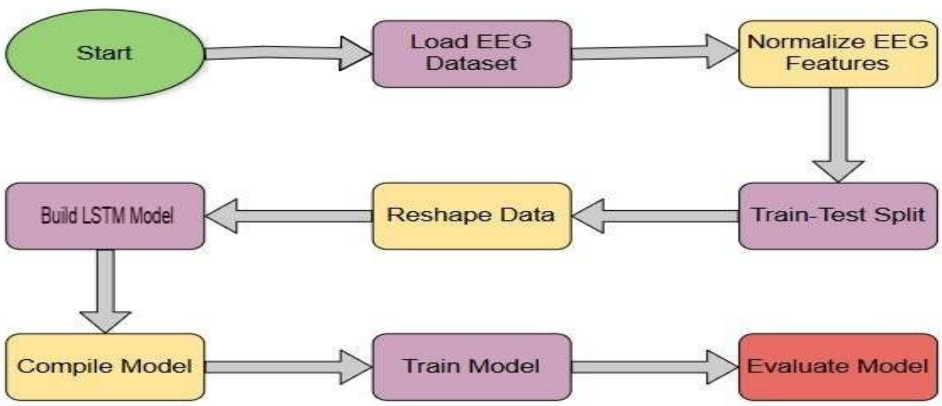

Figure 4.1: Data flow

The process that followed for carrying out emotion recognition using EEG signals via an LSTM-based deep learning process is as follows:

Steps are described stepwise as shown below:

- **Start**

  System environment setup and target identification—emotion recognition from EEG data—are the starting steps.

- **Load EEG Dataset**

  Implementation starts with loading EEG dataset of raw EEG signals for various emotional states. The dataset plays a very crucial role in order to train and test.

- **Normalization of EEG Features**

  EEG data are normalized to normalize feature values on a standard scale.Normalization improves model performance and convergence bypreventing unequal contribution of input features during training.

- **Train-Test Split**

  Normalized data are divided into training and test subsets. Ideally, training setis employed for training models and the test set verifies generalizationcapability of the model for unseen data.

- **Reshape Data**

  Since the LSTM models take the input data in the form of 3D (samples, features, time steps), the data set is reshaped into conformable shape to the same. It is a mandatory operation to reshape it into a conformable shape to the input size of the LSTM network.

- **Create LSTM Model**

  An LSTM model is built. LSTMs are Recurrent Neural Network (RNN) versions that work well on time-series data such as EEG signals because they learn from the sequence in time.

- **Build Model**

  The selected model architecture is subsequently constructed as a model with a suitable optimizer for it (e.g., Adam) and a suitable loss function for the task being carried out (e.g., categorical cross-entropy for classification tasks). This initializes the model to train

- **Train Model**

  Trained model built. Test set is passed through the trained model. During test, model is trained to identify patterns in EEG signals and tag them as such. Batch size and epochs are established in an attempt to control training iterations.

- **Test Model**

  Lastly, test data set is passed through the model. One can test performance as well as model effectiveness validation for emotion recognition from EEG data using Accuracy, precision, recall, F1-score.

4.2 System Design

4.2.1 LSTM (Long Short-Term Memory)

Long Short-Term Memory (LSTM) networks are a class of Recurrent Neural Networks (RNN) that are capable of learning long-term dependencies in sequential data by avoiding the vanishing gradient problem through special gate mechanisms. In each LSTM cell, the following gates control the flow of information:

- **Forget gate:**

  $$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$

  The forget gate determines which information from the previous time step should be discarded.

- **Input gate:**

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

  The input gate controls how much of the new information should be added to the cell state.

- **Output gate:**

  $$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

  The output gate determines which part of the cell state should be output as the final hidden state.

- **Cell state update:**

  $$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t$$

Where:

$$\tilde{c}t = \tanh(W_c[ht-1, x_t] + b_c)$$

The cell state c_t is updated by a combination of the previous cell state and the new candidate cell state $\tilde{c}_t$.

- **Hidden state:**

$$h_t = o_t \cdot \tanh(c_t)$$

The hidden state h_t is the output of the LSTM cell at time step t.

In the EEG emotion recognition model, FFT-transformed EEG features (from `fft_0_b` to `fft_749_b`) are used as input to stacked LSTM layers. As depicted in the architecture diagram, the flow proceeds through two LSTM layers with 128 and 64 units, respectively, followed by dense fully connected layers:

- The first dense layer uses the ReLU activation function to abstract higher-level features.
- The last dense layer applies the Softmax activation function to classify the emotions.

Dropout layers are included to prevent overfitting, and early stopping is implemented to avoid the model from memorizing noise. Standard scaling ensures uniform input ranges, while the FFT transformation minimizes temporal noise by converting EEG signals into frequency components. These combined features enable the model to capture the intricate temporal and spectral patterns essential for robust emotion classification.

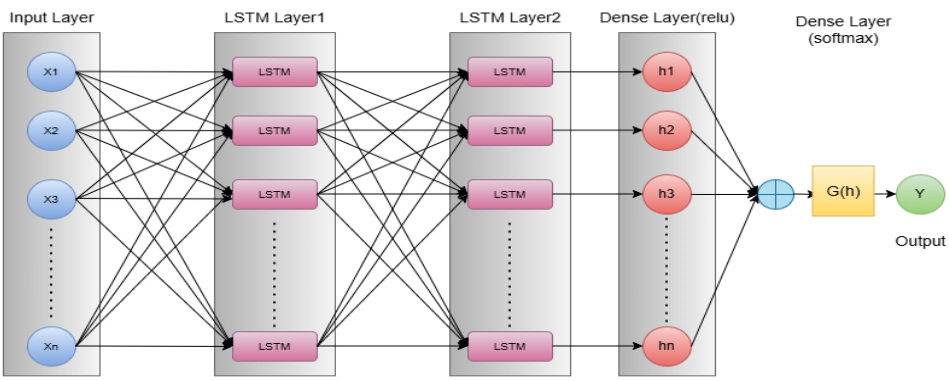

Figure 4.2: LSTM Architecture

4.2.2 FFT (Fast Fourier Transform)

FFT is a processing technique for a signal that maps a time-domain signal to the frequency domain. As EEG signals are time-invariant in nature, FFT aids in the determination of dominant frequencies corresponding to states of emotion. FFT has been utilized here during raw EEG signal processing while 750 frequency features are generated for every sample. These features characterize how brain activity changes with various frequency bands, to which emotional reactions of various types can be traced. Frequency features are the inputs to the LSTM model. FFT enhances the classifier performance and interpretability by emphasizing signal properties of interest.

4.2.3 Dropout

Dropout is one of the regularization methods used to prevent neural network overfitting. The model trains to learn abstract patterns by removing random 50% of its neurons during training so it can avoid memorizing individual training instances and learn 20 additional robust patterns. Dropout layers have been introduced after each LSTM layer with a 30% dropout probability in this project. This prevents the dropout feature power to generalize on unseen EEG data and prevents it from over-relying on individual neurons. Dropout is particularly crucial when dealing with small datasets or deep learning models that have a large number of parameters.

Chapter 5

RESULTS AND DISCUSSION

The EEG-based emotion recognition model developed using an LSTM architecture achieved promising results with a test accuracy of %. To understand the model's performance and how it processes the data, several visualizations and metrics are examined in this section.

The spectral features extracted from the EEG signals using the Fast Fourier Transform (FFT) are visualized in Figure 5.1 . These features represent the frequency domain composition of a singleEEG sample. The oscillatory pattern observed in the plot reflects the underlying brainwave frequencies, which are critical in distinguishing emotional states.

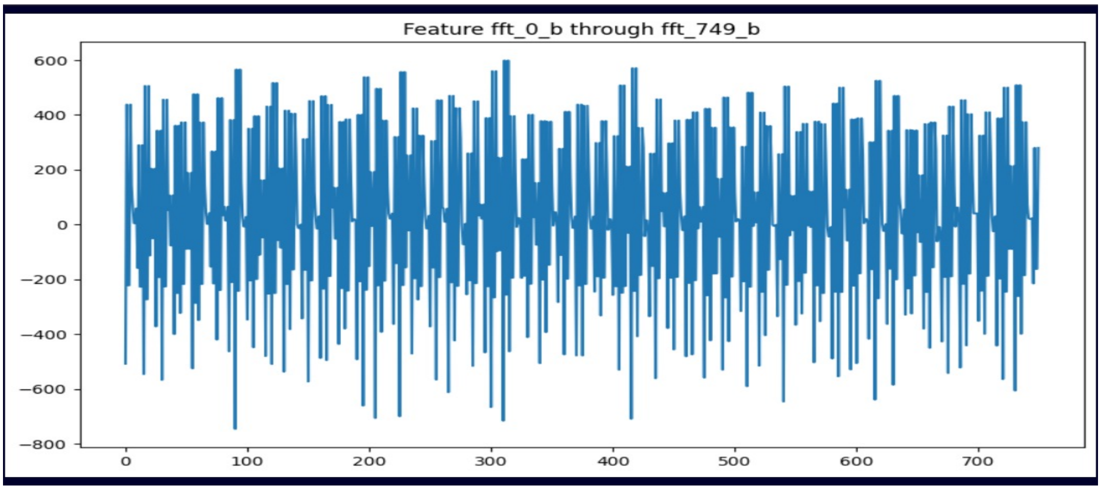

Figure 5.1: Feature fft_0_b through fft_749_b

To gain further insight, an individual EEG signal is plotted in the time/channel domain. As shown in Figure 5.2, the signal labelled with the emotion "Positive" exhibits two significant spikes, which likely indicate neural responses associated with emotional stimuli. Such sharp amplitudes can be characteristic of specific cognitive or emotional events captured during EEG recording.

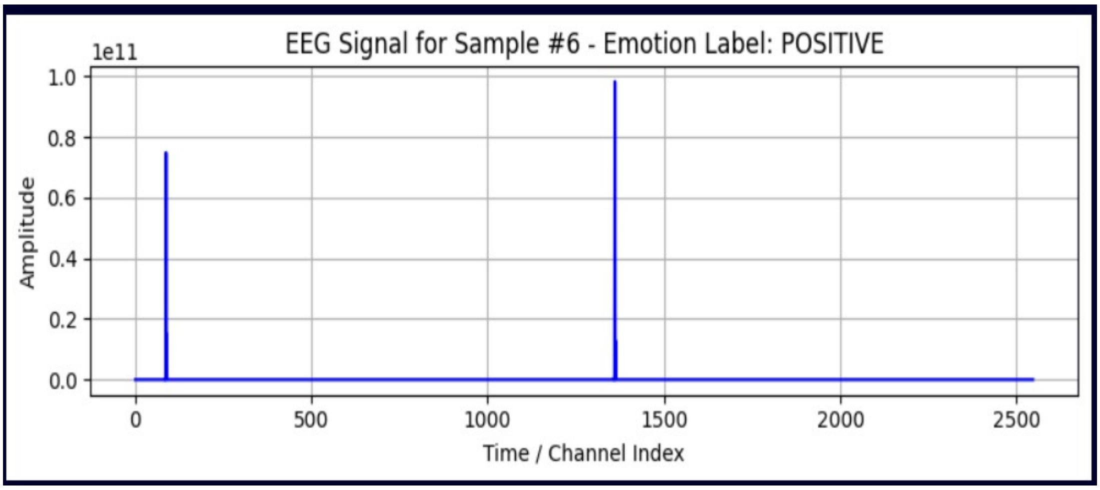

Figure 5.2: Emotion Label

Both training and the validation accuracy after 20 epochs are plotted on the graph shown in Figure 5.3.The steady increase in the accuracies of the initial few epochs indicates that it is learning extremely well. There is a slight fluctuation in validation accuracy between epochs 5 and 10, and this could be due to oscillatory instability or overfitting. It has performed well on new data beyond epoch 10, as can be observed from the training and validation accuracies converging to around 85%.After training, the model typically performs extremely well with little overfitting.

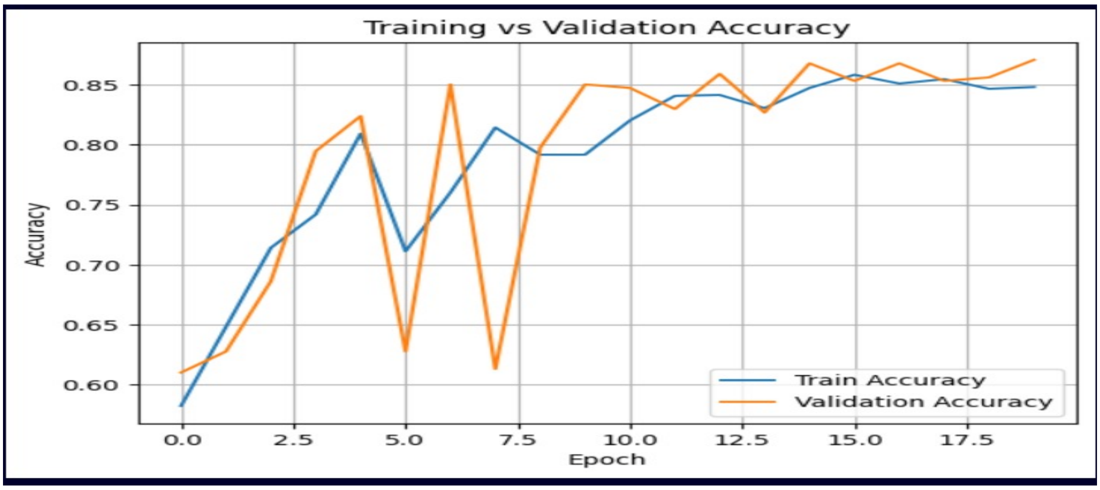

Figure 5.3: Graph Plot

The confusion matrix shown in Figure 5.4, indicates that the model is doing very well in general, particularly in predicting NEGATIVE and NEUTRAL sentiments, where the majority of the predictions are accurate with little confusion. The model, however, appears to struggle with correctly predicting POSITIVE sentiments. There is a significant number of POSITIVE instances being predicted as NEGATIVE, which means that the model might be confusing similar features between these two classes. This indicates that although the model is good in some of the aspects.

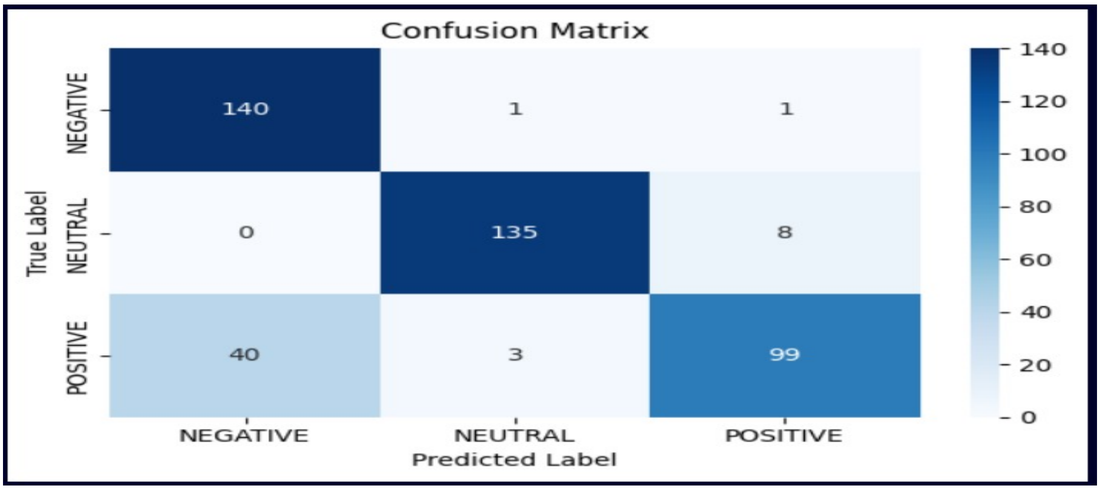

Figure 5.4: Confusion Matrix

Classification Report:

	precision	recall	f1-score	support
NEGATIVE	0.78	0.99	0.87	142
NEUTRAL	0.97	0.94	0.96	143
POSITIVE	0.92	0.70	0.79	142
accuracy			0.88	427
macro avg	0.89	0.88	0.87	427
weighted avg	0.89	0.88	0.87	427

Figure 5.5: Classification Report

The report of classification indicates that the model is extremely overall in performance with accuracy of 88%. The model is at its best within the NEUTRAL class with high recall and precision, followed by good precision for the POSITIVE class but low recall and thus some misclassification in recognizing positive sentiments. The NEGATIVE class exhibits extremely high recall but relatively lower precision, reflecting the fact that it recalls most negative instances but produces some incorrect predictions.

Generally, the model is well-balanced but could perhaps do a better job at differentiating POSITIVE samples properly.

In conclusion, the combination of FFT feature extraction, LSTM modelling, and preprocessing steps such as scaling and label encoding proved to be effective. This approach shows potential for real-time emotion recognition applications. For future improvements, the inclusion of additional modalities (like facial expressions or voice data) or subject-specific personalization could further enhance classification accuracy and robustness.

Chapter 6

CONCLUSION

In conclusion, the research highlights that applying LSTM networks to emotion detection from EEG is actually efficient. In comparision with the traditional ways of trying to interpret someone's emotions, EEG delivers a much simpler and more reliable approach. This is because EEG directly captures neural activity basically, the brain's signal in real time. By evaluating the changes in brain waves as they occur, EEG provides direct glimpes into brain activity.

A common way to analyse these signals is by using a technique called FFT to extract essential features, followed by using LSTM networks to structure how these signals change over time. This combination helps the system to identify complex patterns and relationship within the EEG data that coincide with different emotions. As a result, it can recognize feelings like happiness, sadness, anger and fear with stronger accuracy.The key strength of LSTM networks is their capacity to handle both the time based complexity and high volume of EEG data. This is why they have become widely used and trusted than traditional machine learning methods.Another important point is that various frequency bands of brain activity are interconnected to various emotional states. This makes the model indeed better at predicting emotions based on EEG signals.

In other words, the study shows that the most powerful information about the frequency-domain of emotional brainwave activity is in fact frequency-domain analysis through neural cognizance of the waveform. This will further enhance the model's prescience and will greatly improve the predicted power which, hitherto, the model is not exposed hence showing underexposed neural-emotion models. The new study introduces exciting opportunities for future work in the field of affective computing and real-time emotional intelligence systems. Examples of probable uses include personal mental health surveillance gadgets, emotion-aware adaptable interfaces, and brain-computer interaction systems that adapt to their users' moods in a dynamic and timely manner. The potential of integrating LSTM-based EEG emotion recognition models into wearable technology and the use of edge devices is that real-time and portable emotion detection is practically possible. The health and education sectors, the gaming industry, and even beyond will be profiting from such revolutionary technologies. In essence, the amalgamation of neuroscience and deep learning, as shown in this research, become a part of the main contributors to building emotionally intelligent AI systems capable of deeper, more human-centric interaction.

6.1 Future Work

Facial emotion recognition can be considerably improved by combining facial emotions with EEG based emotion recognition.While facial expression demonstrates visible emotion signals, EEG captures brain signals, providing a more objective understanding of a persons inner emotional state. By combining these two models a multi-modal approach can provide more reliable and accurate observations into human emotions.

This fusion allows a deeper understanding of user perceptions and even detect hidden emotions that are not visible through facial expressions singularly. Such a system has optimistic application in mental health, where identifying delicate emotional expressions is crucial. In education integrating facial expressions with EEG data can help personalized teaching methods to each students emotional state, making learning more specific and effective.

Similarly, in the automotive industry identifying the stress levels using this approach strengthen driver safety.Researchers are also examining deeper emotional patters that often go unexpressed or unnoticed, creating the way for smarter , more responsive systems in various domains.

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