# An Ef·cient Approach to EEG-****** Recognition using LSTM ******

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Abstract·This work aims to investigate the performance of the ******-****** (LSTM) Model for EEG-****** Recognition. For the experimentation, we use the publicly available DEAP dataset, which consists of preprocessed EEG and physiological signals. Our work limits itself to the study of only the EEG signals to have a scope for developing an ef·cient headgear model for real-time monitoring of emotions. In this study, we extract the band power, a frequency-domain feature, from the EEG signals and compare the classi·cation accuracies for Valence and Arousal domain for different classi·ers. The proposed ******-****** (LSTM) model achieves the best classi·cation accuracy of 94.69% and 93.13% for Valence and Arousal scales, respectively, illustrating a signi·cant average increment of 16% in valence and 18% in arousal in comparison to other classi·ers.

Keywords·EEG Data, Emotion, ******, DEAP dataset, Band power, LSTM Network

## I. INTRODUCTION

Emotion represents the state of mind of a person whether a person is happy or sad, angry or calm, stressed, or relieved. Emotions are the response to a particular stimulus. Studies suggest that emotion is a subjective experience: it varies from person to person, and because of this, it is one of the most challenging and exciting research ·elds in psychology [1]. Recognition of emotion plays a vital role in daily life as it can help in enhancing one·s psychological health which is

Skull, according to the 10-20 ******. Since the understanding of the entire EEG signal at once is a complex task, the EEG signal is divided into various frequency bands. The different frequency bands are the Alpha (0-4 Hz), Beta (4-8 Hz), Delta (8-13 Hz), Theta (13-30 Hz), and Gamma (>30 Hz). Each band is associated with different activities taking place in the body. For instance, the Delta wave is related to deep sleep as well as the deepest level of relaxation. Similarly, the Theta wave is associated with REM sleep, deep and raw emotions, and cognitive processing. Likewise, in a drowsy state, the Alpha wave comes into the picture. It is associated with relaxation and calmness. In a conscious state, the Beta wave is present during the thought process. Gamma waves are current when a person tries to perceive two different senses at the same time as sound and sight. EEG signals have broad applications ranging from ****** to diseases and disorders like ******, Epilepsy, and Alzheimer·s disease.

Although various classi·cation techniques have been reported in the literature Alhagry et al. [7] reports a classi·cation accuracy of 85.65%, 85.45%, and 87.99% for valance, arousal, and liking, by using LSTM model. Similarly, Li et al. [8] employed LSTM model achieving a mean accuracy of 76.6%. We compute the band power feature for each frequency band of the EEG signals and employ the machine learning methods, namely ****** Machines (SVM), K-****** (KNN), ******-****** (LSTM), Decision Tree and ******. Section II for ****** presents a detailed description of the previous research work. In this work, we achieve a maximum classi·cation accuracy of 94.69% for valence and 93.13% for arousal using the LSTM classi·er, outperforming the other classi·ers.

In the rest of the paper, Section II describes the related work. Section III contains the proposed methodology, and Section IV includes the experimental results. Finally, we conclude the paper with section V with the conclusion and future work.

## II. RELATED WORK

There are various emotions like happy, excited, angry, afraid, sad, depressed, calm, and contentment and the proper classi·cation of these emotions can be bene·cial for the study. Bastos-Filho et al. [9] have classi·ed the emotional state as calm when the levels of arousal are below 4, and the level of valence is between 4 and 6. Similarly, for stress, the levels of arousal should be greater than 5, and that of valence should be less than 3.

In researches concerning the problem of emotion classi·-cation, the ability to classify emotions depends on two main factors:

1) Features extracted from the dataset.
2) Classi·ers used for emotion classi·cation.

The classi·cation accuracy compared to the original dataset can be improved by extracting a wide range of features from

Alhagry et al. [7] have proposed an end-to-end model employing the LSTM classi·er for emotion classi·cation on the DEAP dataset. The average subject-independent accuracy achieved for arousal, valence, and liking is 85.65%, 85.45%, and 87.99%.

Li et al. [8] have used RASM as a feature which represents frequency-space domain characteristics of the EEG signal. They have employed the LSTM model on DEAP dataset and achieved a mean accuracy of 76.6%. Xing et al. [17] built ****** (SAE) for EEG signal decomposition and used LSTM model for classi·cation but still observed accuracy of 81.1% in valence and 74.38% in arousal.

Yang et al. [18] propose a parallel combination of Convolutional ****** and LSTM Network to extract features from the DEAP dataset and then use the softmax classi·er for classi·cation. This model obtained the mean accuracy of 90.80% and 91.03% for valence and arousal.

Previous works in the ****** establish that the LSTM models perform better than other classi·cation techniques. Still, the reported work examines either the raw EEG signals or the time-domain features for training the LSTM model. Here, we investigate the use of the band power, a frequency-domain feature for training the LSTM model. To compare the performance of the proposed LSTM model with other classi·ers, we also train classi·ers, namely SVM, KNN, ******, and ******. On contrasting the results, we observe a maximum classi·cation accuracy of 94.69% for valence and 93.13% for arousal using the LSTM classi·er, which is signi·cantly better than other classi·ers.

## III. METHODOLOGY

### A. ******

The DEAP dataset [12] is a multimodal dataset for the determination of human emotional states available for public access. For the creation of the database, experiments were performed where 32 participants were made to watch 40 one-minute-long excerpts of selected videos, during which the signals from 32 channels of standard EEG headset and physiological signals from 8 channels were captured. Equipment had a sampling frequency of 128 Hz. The data was pre-processed, and artefacts were removed. The participants rated each video on a scale of 0-9 in terms of valence, arousal, dominance, and liking. These ratings become the benchmark for the classi·cation of emotional states.

### B. Pre-processing

Fig. 1 illustrates the EEG signals for two subjects (1, and 9) subjected to the same trial. Both signals indicate differences in the magnitude and the pattern of activations of the brain for different individuals. Thus, it displays the uniqueness in the processing of information in the brain for every individual.

Fig. 2 illustrates the EEG signals for a single person, subjected to two different trials. Both signals display similarity

Fig. 3. Proposed LSTM Model
it does possess useful information regarding the state of mind of the individual before showing video trials. The band power for the different bands is calculated using the Welch method based on the Hanning window. The window length here is 1s and the stride of 0.25s for the entire 63s, therefore, obtaining 249 band power values at different instances of time. Only the EEG data values are used for experimental purposes, as our long term goal is to develop a real-time emotion prediction model where we require a minimal amount of hardware so that it can be used in the daily lives of every individual, especially patients.

C. LSTM ****** this paper, we use the LSTM network as a useful tool for the prediction of the emotion of individuals. The LSTM networks are frequently used for handling sequential data such as paragraphs in NLP, previous electricity load in the case of the electricity demand prediction. LSTM cell possesses the ability to remember the distant as well as recent events to accurately predict the target variable. This property of retention can turn to be useful for emotion recognition as knowing about the past activations of the EEG signals can drastically affect the prediction of target variables and provide useful insights to the events leading to an appropriate response for the subject.

Fig. 3 shows the con·guration of the Proposed LSTM model. We implement the model in Python 3 on the ****** platform with GPU support for the LSTM network. LSTM layer has 40 nodes. Dense 1 layer has 10 nodes with ·tanh· activation function, and Dense 2 has a single node with ·sigmoid· activation function. We use a Dropout 25% between the LSTM Layer and Dense 1 Layer. We use ******-dient Descent (SGD) optimizer (learning rate=0.01, learning rate decay constant=1 ·10·5, and momentum constant=0.9) to minimize the binary-cross-entropy loss function.

Other than the customized LSTM model, we also test the classi·cation on the dataset using KNN, SVM, ******, and ******. We evaluate the performance of each classi·er on the pre-processed dataset. As expected from the previous studies, the proposed LSTM model outperforms the other classi·ers by a huge margin.

IV. RESULTS

To verify the effectiveness of the proposed LSTM model, we contrast the performance of KNN, SVM, ******, ******, and LSTM models for classi·cation of the preprocessed dataset. We test models several times to ensure the signi·cance of the results observed. Table I highlights the average prediction accuracies.

TABLE I

TESTING ACCURACIES

******

Arousal

KNN

·ve bands of frequencies, namely Alpha, Beta, Gamma, Delta, and Theta, to derive the band power of each band. We use band power as a feature for classifying valence and arousal of the subject. We evaluate and compare using KNN, SVM, ******, ******, and LSTM as our classi·ers.

On analysis, we observe a minimum average increment of 16% in the average testing accuracies and maximum classi·cation accuracy of 94.69% for valence and 93.13% for arousal using the LSTM classi·er, which performs better than the current state-of-the-art classi·ers.

In future, we can use the proposed experimental setup to obtain useful information regarding the emotions of the subjects and extend it for real-time applications. For further improvements, we can add more frequency domain features and test for their performance. As demonstrated by Wichakam and Vateekul [15], a subset of the channels for feature generation may perform better in terms of accuracy. The work may further be extended to include subject-independent models as well. The study can be also be extended to developing 3-D emotion models like the work of Dabas et al. [13].

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