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EMOTION RECOGNITION USING ELECTROENCEPHALOGRAPHY (EEG) SIGNALS BY DEEP LEARNING TECHNIQUES

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***ABSTRACT-* Emotion recognition has received considerable attention over the last decade as it is directly linked to psychology, physiology, learning studies, marketing and healing. In this project, we comparatively analyze the emotions by using EEG signals (Electroencephalography) by means of "Deep Learning Techniques". The primary objective of this project was to analyze the emotions by using EEG signal datasets and applying a novel Deep Learning techniques such as Gated Recurrent Unit (GRU), Long Short-term Memory Networks (LSTM) and Deep neural network (DNN) models. These algorithms tend to analyze the emotions like Valence, Arousal and Likely.**

Keywords - GRU, LSTM, DNN

I. INTRODUCTION

In human contact, emotion is very crucial. Attributes like words, voice intonation, facial expressions, and kinesics can all be used to portray one's feelings. However, brain-computer interface (BCI) devices have not yet reached the level required for emotion interpretation. With the rapid development of machine learning algorithms, dry electrode techniques, and different real-world applications of the brain-computer interface for normal individuals, emotion categorization from EEG data has recently gotten a lot of attention. Electroencephalogram (EEG) signals are a critical resource for these systems. The primary benefit of employing EEG signals is that they reflect true emotion and are easily resolved by computer systems. In this work, EEG signals associated with valence, arousal, likely emotions were identified using dataset.

II. RELATED WORK

In reference [1] a standard pre-processed Database of Emotion Analysis using Physiological signalling (DEAP) was used in this work. The statistical features, wavelet features, and Hurst exponent were extracted from the dataset. The feature selection task was implemented through the Binary Gray Wolf Optimizer. At the classification stage, the stacked bi-directional Long Short-Term Memory (Bi-LSTM) Model was used to recognize human emotions. In this paper, emotions are classified into three main classes: arousal, valence and liking. The proposed approach achieved high accuracy compared to the methods used in past studies, with an average accuracy of 99.45%, 96.87% and 99.68% of valence, arousal, and liking, respectively, which is considered a high performance for the emotion recognition model.

In reference [2] an emotion recognition system is developed based on valence/arousal model using electroencephalography (EEG) signals. EEG signals are decomposed into the gamma, beta, alpha and theta frequency bands using discrete wavelet transform (DWT), and spectral features are extracted from each frequency band. Principle component analysis (PCA) is applied to the extracted features by preserving the same dimensionality, as a transform, to make the features mutually uncorrelated.

Support vector machine (SVM), K-nearest neighbor (KNN) and artificial neural network (ANN) are used to classify emotional states. The cross- validated SVM with radial basis function (RBF) kernel using extracted features of 10 EEG channels, performs with 91.3% accuracy for arousal and 91.1% accuracy for valence, both in the beta frequency band.

In reference [3] a novel deep neural network is proposed for emotion classification using EEG systems, which combines the Convolutional Neural Network (CNN), Sparse Auto encoder (SAE), and Deep Neural Network (DNN) together. In the proposed network, the features extracted by the CNN are first sent to SAE for encoding and decoding. Then the data with reduced redundancy are used as the input features of a DNN for classification task. The public datasets of DEAP and SEED are used for testing. Experimental results show that the proposed network is more effective than conventional CNN methods on the emotion recognitions. For the DEAP dataset, the highest recognition accuracies of 89.49% and 92.86% are achieved for valence and arousal, respectively. For the SEED dataset, however, the best recognition accuracy reaches 96.77%.

In reference [4] to improve the performance of emotion recognition using brain signals by applying a novel and adaptive channel selection method that acknowledges that brain activity has a unique behaviour that differs from one person to another and one emotional state to another. Moreover, we propose identifying epochs, which are the instants at which excitation is maximum, during the emotion to improve the system's accuracy. We used the zero-time windowing method to extract instantaneous spectral information using the numerator group-delay function to accurately detect the epochs in each emotional state. Different classification scheme were defined using QDC and RNN and evaluated using the DEAP database. The experimental results showed that the proposed method is highly competitive compared with existing studies of multi-class emotion recognition. The average accuracy rate exceeded 89%.

In reference [5] the EEG data of 8 channels were inputted into the LSTM and Bi-LSTM models to classify positive and negative emotions. The recognition highest accuracy rate of the two models was 90.8% and 95.8% respectively. The four-channel EEG data based Bi-LSTM also reached 94.4%.

III. PROPOSED METHODOLOGY

We used "emotions.csv" dataset for emotion recognition using Electroencephalogram (EEG) signals for more accuracy. By usage of DEAP dataset we choose the best algorithm among the three. They are (Fig.1) Gated Recurrent Unit (GRU), Long Short-term Memory Networks (LSTM) and Deep Neural network (DNN) models. We train and split the data for classification and feature extraction using three algorithms By comparing the accuracy of these various algorithm that can fit for our model with high accuracy.

- **Dataset**- The dataset named as "emotions.csv" with records count as 2133 was used. Dataset has been processed with our original strategy of statistical extraction. The data was collected from two people (1 male, 1 female) for 3 minutes per state positive, negative, neutral. We used a Muse EEG headband which recorded the TP9, AF7, AF8 and TP10 EEG placements via dry electrodes. For 22 participants frontal face video

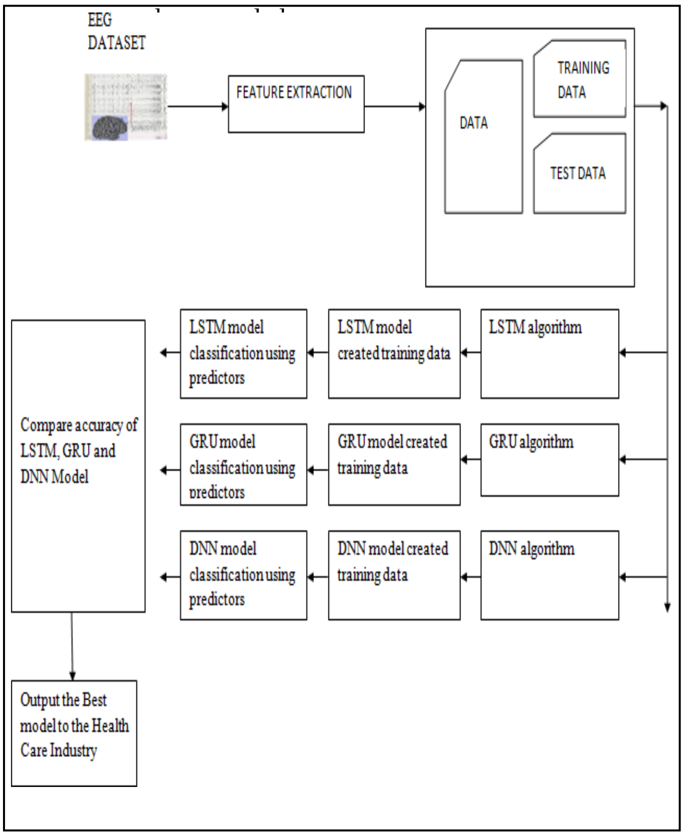

Fig. 1 Architecture of Proposed Model

A. *LSTM – LONG SHORT-TERM MEMORY:*

Long Short-Term Memory (LSTM) is also a type of Recurrent Neural Network (RNN) that is specifically designed to handle sequential data, such as time series, speech, and text.

LSTM networks are capable of learning long-term dependencies in sequential data, which makes them well suited for tasks such as language translation, speech recognition, and time series forecasting.

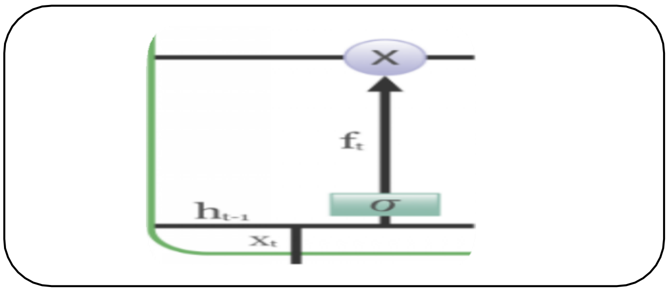

Fig. 2 Forget Gate

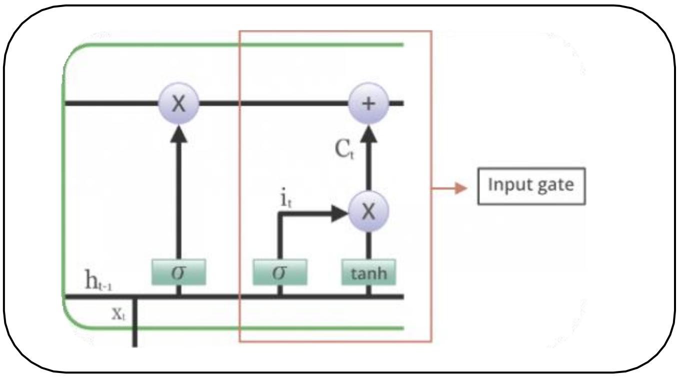

Fig. 3 Input Gate

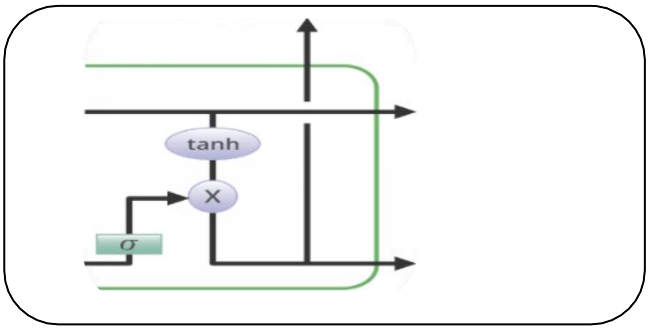

Fig. 4 Output Gate

The LSTM model works well with sequential data, where the model needs to preserve the context of long-sequence as it can be seen from Fig. 2, 3, 4. A LSTM unit mainly has four gates, (i) input gate (It), (ii) output gate (Ot), (iii) forget gate (Ft) and (iv) memory unit (ct). The role of (It) is to fetch the data into the model; the received data is processed by LSTM model and separated the useful data from the raw. Next, it is the forget gate (Ft) responsibility to throw out the irrelevant data from the cell state. Mathematically, the forget gate is defined by Eq. 1:

Ft = σ (Wf [rt−1, it] + Bf) (1)

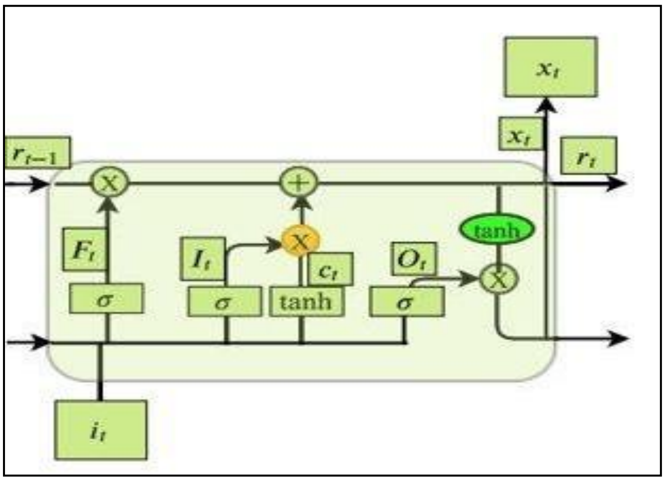

Fig. 5 LSTM

Where Wf is the weight, r(t−1) is the output from the previous timestamp, it is the new input message word, and Bf is the bias. The stored data from the previous unit and the current input data is further processed in two steps as can be seen from Fig. 5. The input gate It and the tanh layer processed the data and generate ct which added with the It values. thect and it are calculated by the Eq. 2, and Eq. 3:

ct = tanh (Wc[ht−1, it] + Bc) (2)

It = σ (WI [ht−1, it] + BI) (3)

After this, the previous unit information rt−1 is updated to new information rt which is defined (Eq. 4):

rt = Ft ∗ rt−1 + It ∗ ct (4)

At last, the output gate Ot (Eq. 5) values is decided with the help of sigmoid layer. To do so, the ct value is passed with tanh function and multiplied with Sigmoid activation function.

Ot = σ (WO [Ht−1, it] + BO) (5)

Xt = Ot * tanh(ct) (6)

B. *GRU – GATED RECURRENT UNIT:*

The Gated Recurrent Unit (GRU) is a type if Recurrent Neural Network (RNN) that, in certain cases, has advantages over long short term memory (LSTM). GRU uses less memory and is faster than LSTM, however LSTM is more accurate when using datasets with longer sequences.

The gating mechanisms are used **to control the flow of information in and out of the network**. The GRU has three gating mechanisms, called the **reset gate, update gate** and **current memory gate** as seen from Fig. 6.

Update Gate(z): It determines how much of the past knowledge needs to be passed along into the future. It is analogous to the Output Gate in an LSTM recurrent unit.
Reset Gate(r): It determines how much of the past knowledge to forget. It is analogous to the combination of the Input Gate and the Forget Gate in an LSTM recurrent unit.
Current Memory Gate (ht): It is often overlooked during a typical discussion on Gated Recurrent Unit Network. It is incorporated into the Reset Gate just like the Input Modulation Gate is a sub-part of the Input Gate and is used to introduce some non-linearity into the input and to also make the input Zero-mean. Another reason to make it a sub-part if the Reset gate is to reduce the effect that previous information has on the current information has on the current information that is being passed into the future.

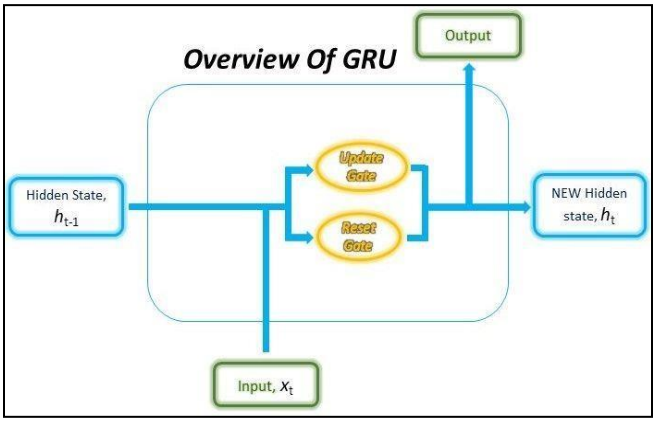

Fig. 6 GRU

C. *DNN – DEEP NEURAL NETWORK:*

A Deep Neural Network (DNN) is an ANN with multiple hidden layers between the input and output layers. Similar to shallow ANNs, DNNs can model complex non-linear relationships.

The main purpose of a neural network is to receive a set of inputs, perform progressively complex calculations on them, and give output to solve real world problems like classification. We restrict ourselves to feed forward neural networks as seen from Fig. 7.

We have an input, an output, and a flow of sequential data in a deep network. Neural networks are widely used in supervised learning and reinforcement learning problems. These networks are based on a set of layers connected to each other.

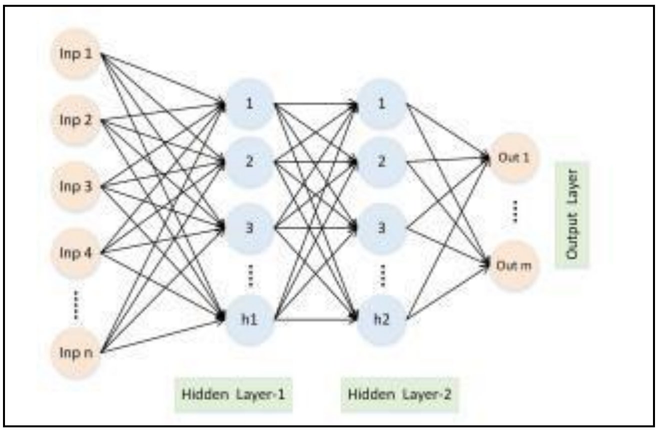

Fig. 7 DNN

The formula for single neuron in a DNN can be expressed:

$$Z = B+\sum(X*W)$$

Z is the output of the neuron

B is bias term (a constant value that adjust the output)

X is the input vector (a vector of values from the previous layer)

W is the weight vector (a vector of weights that corresponds to each input)

IV. EXPERIMENTAL RESULTS

We trained LSTM, GRU and DNN classifier with pre-processed DEAP dataset. Table 1 shows the cross-validated accuracy of the classifiers. Hence, the dataset is not balanced so we use the performance metrics Precision, Recall, F1 Score. And the result we observed is,

MODEL	PRECISION	RECALL	F1	ACCURACY
LSTM	0.96	0.96	0.96	0.96
GRU	0.97	0.97	0.97	0.97
DNN	0.98	0.98	0.98	0.98

Table 1 – Result

From this observation, for the performance metrics **DNN** has the higher accuracy among all other models.

V. CONCLUSION

The task of emotion recognition faces many challenges due to Instability and complexity of EEG Signals. This research provided an effective solution for emotion recognition model. The deep learning based approach was proposed to improve the accuracy of emotion recognition based on EEG Signals. We observed high accuracy for the three algorithms LSTM, GRU and DNN as 0.96%, 0.97%, and 0.98%.

VI. FUTURE WORK

In future research other classification algorithms can be applied on DEAP and other datasets to prove their effectiveness in emotion recognition system and also we suggest to use different techniques to measure brain signals such as Functional Magnetic Resonance Imaging (FMRI)**.**

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