EMOTION CLASSIFICATION OF EEG BRAIN SIGNAL USING DEEP LEARNING AND RNN

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Abstract— Due to the advancement of brain research and biomedical science, the fast growth of electroencephalogram (EEG) signal analysis tools, the use of EEG data to track human health has become increasingly common in the recent decade. Electroencephalography (EEG) is one of the most common tools for studying the human brain's comprehensive activity system. Emotion is important for understanding each other in communicative activities in everyday life. Because of the factuality of emotion representation, the electroencephalogram (EEG) depending on emotion detection has been applied in many fields of diverse disciplines. Eye activities, blinks, heartbeat activity, and muscular action are examples that all impact EEG data and affect cerebral function. On an EEG brainwave dataset, we conducted experiments using two models: Deep Learning and RNN with GRU. We also used different hyper parameters, like epochs, batch size, and optimizers to influence the outcomes. According to the experimental results, the recurrent neural network model with different hyper parameters such as epochs, batch size and optimizers improves the efficiency of the existing deep learning algorithm.

Keywords— EEG signal, RNN Model, Neural Network, Emotion Detection , Deep Learning, LSTM, GRU

I. INTRODUCTION

Healthy humans have varied brainwave frequencies in various sensory situations. These rhythmic brainwaves have a distinct sensitivity and are frequently altered by activities and ideas [1]. The brain-computer interface (BCI) system allows neural impulses conveying the customer’s intention to communicate with device control signals. The EEG [2] is the most widely used basic wave to represent the brain frequency band division and the various kinds of brainwaves that represent mental processes in the brain. The electroencephalogram (EEG) is a signal that is commonly applied to achieve neural signals. Deep learning effectiveness is negatively affected by EEG diversity among people in EEG decoding [3].

Emotion recognition based on biological brain signals involves the use of convenient and accurate signal processing and feature extraction techniques [4]. Existing approaches extract meaningful information from a set number of electroencephalography (EEG) channels using a variety of methodologies. The goal of this research was to improve emotion recognition using brain signals by employing a new and flexible channel selection strategy that recognizes that brain activity has a distinct behavior that varies from individual to individual and one emotional state to other. Furthermore, to enhance the system's accuracy, we recommend distinguishing epochs, which are the times when excitation is at its peak, during the emotion. To properly determine the epochs in each emotional state, we employed the zero-time windowing technique to extract instantaneous spectral information and the numerator group-delay function. Using QDC and RNN, different categorization schemes were designed and assessed using the DEAP database.

The rest of this paper is arranged in the following manner. The related work of the system is covered in Section 2. Section 3 describes the dataset used. The Section 4 is a Methods used for predicting sentiments from EEG brainwaves. The outcomes of experiments are discussed in Section 5 to demonstrate the efficiency of the deep learning algorithm. Section 6 concludes with conclusions and recommendations for future work.

II. RELATED WORK

J. J. Bird et al. [5] explores the idea of employing evolutionary computation to both choose effective discriminative EEG features and optimize the architecture of Artificial Neural Networks, suggesting a new method for EEG data classification. From a starting collection of 2550 EEG statistical data, an evolutionary method is used to pick the most significant features. Before classification, an evolutionary strategy is used to optimize a Multilayer Perceptron (MLP) in order to estimate the network's optimum hyper parameters. Deep learning and tuning with Long Short-Term Memory (LSTM) are also investigated, and for each scenario, Adaptive Boosting of the two kinds of models is evaluated. Three experiments with different classifiers are offered for comparison: one for attention state classification, one for emotional sentiment classification, and a third test in which the objective is to estimate the number that the individual is considering. The findings shows that on the attention, emotional, and numerical datasets, an Adaptive Boosted LSTM can reach precision of 84.44 percent, 97.06 percent, and 9.94 percent, respectively. For the first two tests, an evolutionary-optimized MLP gets results that are similar to the Adaptive Boosted LSTM, but significantly higher for the number-guessing experiment, with an Adaptive Boosted Deep Evolutionary (DEvo) MLP achieving 31.35 percent and being significantly faster to train and categorize. In the same standards, the precision of the nonboosted DEvo MLP was 79.81 percent, 96.11 percent, and 27.07 percent.

Emotions play a crucial role in a person's day-to-day life. Assessing human emotions using an electroencephalogram (EEG) has become a difficult task in recent years. The depiction of human brain electrical activity is a key component of the EEG signal. The processes of emotion elicitation stimulation, namely, gathering or development of the database, pre-processing, feature extraction, feature reduction or selection, and classification, are followed in the emotion detection utilizing EEG signal. In this research, the raw EEG data are transformed by utilizing an adaptive FIR filter with a Least Mean Square (LMS) optimization technique, and the processed signal is divided into four separate EEG frequency bands that use the Daubechies Wavelet Transform. These frequency bands are used to derive various statistical data. To recognize discrete emotions (angry, cry, happy, and sad) of a human being using EEG signal, a combination of Adaptive Filter (Finite Impulse Response, FIR), Time-Frequency Analysis (Daubechies Wavelet Transform), and Support Vector Machine (SVM) classifier is employed by P. S. Ghare and A. N. Paithane [6].

In recent times, researchers have focused their efforts on developing EEG-based Brain-Computer Interfaces (BCI) to improve wellbeing of individuals through medical applications. BCIs can also be utilized to give a more customized experience for consumers in advertising, game, and infotainment. The capability to assess the user's multimedia-induced cognition and emotional experience is required in both medical and non-medical applications. aWith a single-channel commercial BCI device, M. A. Sarkaya and G. Ince [7] demonstrate a unique approach to detect human emotion. A deep learning neural network was used to evaluate the suggested EEG-based emotion identification system on human test participants, and accuracy of over 87 percent was attained.

Recognizing human emotion is a critical element for machines to improve communication in the areas of Human Interaction (HMI). M. A. Abdullah and L. R. Christensen [8] use five distinct models to examine 10 different emotions depending on Arousal, Dominance, and Valance, as well as new filters relying on Riemannian geometry to improve categorization. EEG signals are gathered and fed into the proposed models, with recognition rate ranging from 50% to 70%. For each topic, two sessions were held to gather data for training and testing the systems. The training data was tagged using the SAM evaluation approach. Regarding the dataset for the models, which used to be one session, the models were capable of creating a very high level of height accuracy; however, the author's discovered that model generation is a time-consuming task due to the numerous models being trained per subject, which can be improved in the additional training phase by concentrating on the most appropriate model. The efficiency will be improved by modifying the arrangement to include multiple training sessions and only one testing session. Finally, it is preferable to consult an ethics board and obtain written consent instead of verbal approval when collecting this data.

The merging of hundreds of brain neurons causes a change in electrical potential, which is reflected by a brainwave. When enough energy is gathered, a neuron receives information from neighbouring neurons and initiates a cyclic discharge process. That is also why individuals emit brainwaves on a regular basis. As per specialists at Michigan University's Laboratory of Brain Recognition and Behaviour, long-term multitasking activity outcome in a loss of performance and in filtering out insignificant signals, which leads to the diversion of paying attention to the irrelevant message rather than work-related data.

As a result, transitioning from one job to another would be difficult. Some individuals, on the other hand, depend on their intellect to handle a variety of tasks, which can lead to exhaustion. As a result, C. Y. Liao et al. [9] conducted this experiment in order to determine the most effective technique to ease spiritual pressure and quiet the mind. A deep learning algorithm is used by authors to estimate a user's stress level by listening to music. According to the findings, listening to music or creating a music environment with an artistic presentation can provide not only a psychological therapy impact but also enhance a person's opportunity to concentrate.

Emotions are expressive events that vary over time and are generated by stimuli. Videos and films, in particular, are intended to trigger emotional responses from their viewers. Finding the emotional imprints of videos can be achieved by finding the viewers' emotions in real time. M. Soleymani et al. [10] present a method for identifying the emotions of video viewer’s emotions in real time .Signals from the electroencephalogram (EEG) and facial expressions Respondents were shown a series of emotional videos while they were on the treadmill. The respondents' facial expressions and physiological responses were captured on film. The video’s stated valence (negative to pleasant feelings) five annotators annotated the faces of the participant’s respondent. The valence and arousal dimensions of the stimulation videos were also continually annotated. In order to recognize emotions automatically and constantly, the researcher used long-short-term memory recurrent neural networks (LSTM-RNN) and Continuous Conditional Random Fields (CCRF). They discovered that the findings obtained from facial expressions were superior to those obtained from EEG signals. They investigated the impact of facial muscle activity contamination on EEG signals and discovered that this contamination is responsible for the majority of the emotionally valuable material in EEG characteristics. In the context of facial expressions, however, their statistical study revealed that EEG signals still provide additional information.

III. DATASET

This is an EEG brainwave data collection that has been analyzed using initial statistical extraction approach. Because waves must be mathematically defined in a periodic manner, the statistical extraction technique resampled the data. Data were collected for 3 minutes from two participants (1 male, 1 female) in each state - positive, neutral, and negative [11]. J. J. Bird et al. [12] used a Muse EEG headgear with dry electrodes to capture the TP9, AF7, AF8, and TP10 EEG locations. The triggers used to elicit these emotions are listed below, along with six minutes of resting neutral data.

1 . Marley and Me - Negative (Twentieth Century Fox)
Death Scene

1. Up - Negative (Walt Disney Pictures)
   Opening Death Scene
2. My Girl - Negative (Imagine Entertainment)
   Funeral Scene
3. La La Land - Positive (Summit Entertainment)
   Opening musical number
4. Slow Life - Positive (BioQuest Studios)
   Nature timelapse
5. Funny Dogs - Positive (MashupZone)
   Funny dog clips

IV. METHOD

A. Deep Learning

Deep learning is a type of machine learning approach that focuses on deep learning data models. For feature extraction and transformation, it primarily employs architecture with a large number of deep hidden layers and non-linear processing units [13]. Deep learning has the ability to automatically extract the sophisticated characteristics required for classification and can directly interpret and train complicated signal representations of the original signal. Deep learning algorithms use a deep architecture with numerous hidden layers to learn several levels of description of raw data automatically. This algorithm extracts the high-level features required for classification, which include more significant data that is hierarchically dependent on other features [14].It has been extensively used in diverse areas of research such as voice recognition, object recognition, and language translation in the last ten years, has been progressively used in EEG signal interpretation. At the moment, convolutional neural networks (CNNs), depth of belief networks (DBNs), auto encoders (AEs), and recurrent neural networks (RNNs) are the most widely utilized depths in EEG signal decoding learning algorithms.

B. Recurrent Neural Network(RNN)

A RNN is a type of neural network that has the ability to remember things for a brief period of time. The neurons in the hidden layer of the RNN get input information from other neurons, but they can also receive output information earlier themselves, establishing a network structure with circulation. The RNN is more similar to the design of a biological neural network when compared with the feed-forward neural network. The Back Proportion algorithm can be used to learn and optimize the parameters of a recurrent neural network. The back-propagation algorithm conveys error info in reverse chronological order, one step at a time. RNN is based on the Hopfield model; however it is still in its development. The emergence of deep learning theory has accelerated the development of recurrent neural networks. The most significant advantage of RNN is that it can retain past data [15]. It can detect long-term dependencies between events isolated by time series and run in a way that distributes weight across time. As a result, RNN differs from other deep neural networks in that it can handle time-series data.

Conventional LSTM:

Long Short-Term Memory (LSTM) is a recurrent neural network (RNN) architecture that was created to better precisely simulate periodic sequences and their long-range dependencies have more precision than traditional RNNs. Figure 1 represent the architecture of LSTM RNN. In the recurrent hidden layer of the LSTM, there are memory blocks, which are special units. Memory cells with self-connections store the network's temporal state, while special multiplicative units called gates govern the flow of data in the memory blocks. In the original architecture, each memory block had an input gate and an output gate. The flow of input activations into the memory cell is controlled by the input gate. The output gate regulates the flow of cell activations throughout the network. The forget gate was eventually added to the memory block [16].The forget gate dynamically forgets or resets the cell's memory by scaling the internal state of the cell before providing it as input to the cell through the cell's self-recurrent link. Furthermore, the contemporary LSTM architecture includes peephole connections between internal cells and gates within the same cell to learn accurate output timing.

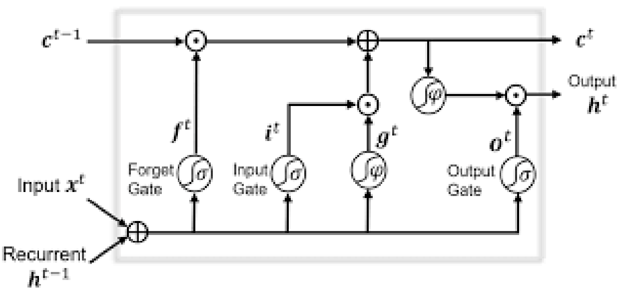

Figure 1: LSTMP RNN architecture

C. Gated Recurrent Unit (GRU)

GRU networks are RNNs, which are neural networks with at least one cycle are in their underlying structure of inter neuronal connections. They were first presented in 1997 and refined over the years. GRU is a type of gated RNN that is used to tackle the problem of vanishing and expanding gradients in traditional RNNs when training long-term dependencies [17]. The input layer, as shown in Figure 2, is made up of many neurons, the number of which is dictated by the size of the feature space. Consequently, the output layer's number of neurons correlates to the output space. The GRU networks' major functions are covered by the hidden layer(s) comprising memory cells.

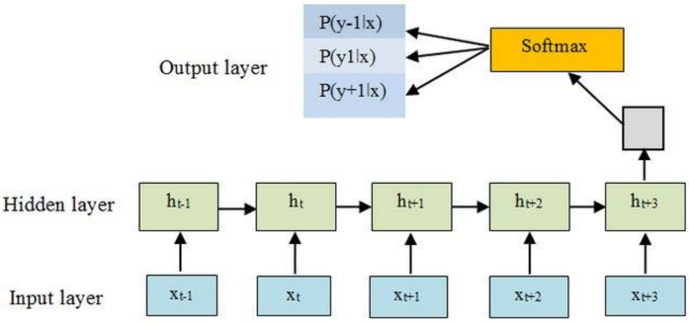

Figure 2: Structure of GRU-based model.

V. EXPERIMENT AND RESULT

We used two models, Deep Learning and RNN with GRU, to undertake experiments on an EEG brainwave dataset. Two hidden layers are used in the Deep Learning model. To increase the model's performance, a Recurrent Neural Network (RNN) with Gated Recurrent Unit (GRU) is used. For both models, we also demonstrate the impact of several hyper parameters such as epochs, batch size, and optimizers. Confusion Matrix, Precision, Recall, F1-Score, and Support are some of the assessment measures that we have utilized in our experiment.

A. Load Dataset

We start with loading of EEG dataset from input directory. The EEG dataset files available in CSV format. To have a stronger insight of the dataset, we utilize Pandas to examine the data in the form of DataFrame. Figure represents the visualization of the EEG Dataset readings from fft_0_b to fft_749_b columns.

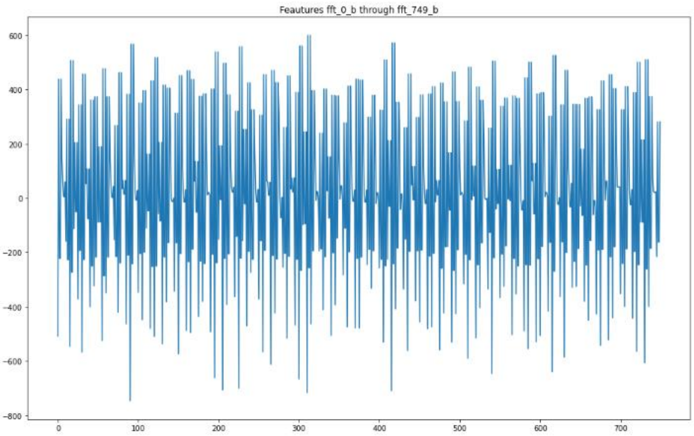

Figure 2: EEG Dataset readings from fft_0_b to fft_749_b columns.

B. HYPER PARAMETER FOR MODEL

- Epochs: The number of epochs is the total number of times the training dataset has been traversed. The number of epochs can be set to anything from one to infinity. You can run the method indefinitely and even terminate it using factors other than a predetermined number of epochs, such as a change in model uncertainties over the period.
- Batch Size: The batch size parameter has an impact on the model's performance. Larger batches demand longer training time and have an impact on memory requirements as well as overall efficiency. As a result, choosing the right batch size is critical for improving model quality.
- Optimizers: Another major consideration is to select an optimizer that improves the performance of the model. It updates the weight parameter, which reduces the loss function. Our goal is to lessen the loss of neural networks by modifying the network's configurations. The actual and predicted values are compared to evaluate the neural network loss function. To determine the best optimizer, four optimizers are evaluated and their accuracy is compared. Stochastic gradient descent (SGD), Adam, Adagrad, and RMSprop are the four optimizers employed in this paper.

C. Performance Analysis of Deep Learning

In this model we use basic deep learning model with one input layer, two hidden layers and one output layers. Figure 3 shows the impact of epochs in deep learning Model. The model is trained at different numbers of epochs 50, 80, 100, 130, and 150 after selecting the batch size 32, and Adam Optimizer. Figure shows that model achieved the highest accuracy at 80 epochs.

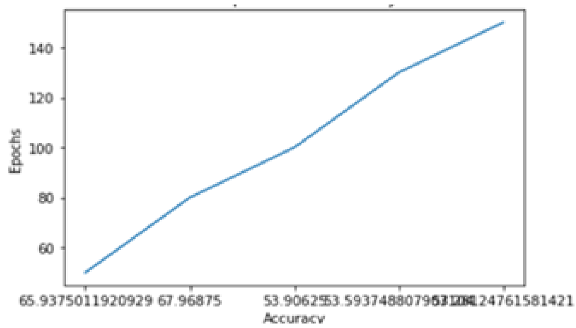

Figure 3: Impact of Epochs in Deep Learning

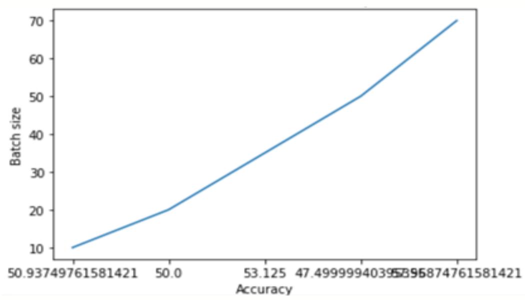

Figure 4: Impact of Batch Size in Deep Learning

Figure 4 represent the impact of batch size in deep learning Model. The model is trained at different batch size 10, 20, 35, 50, and 70 after selecting the epoch 150, and Adam Optimizer. It is clear from the figure the accuracy of model increases as the batch size increases. Figure shows that model achieved the highest accuracy at 70 batch size.

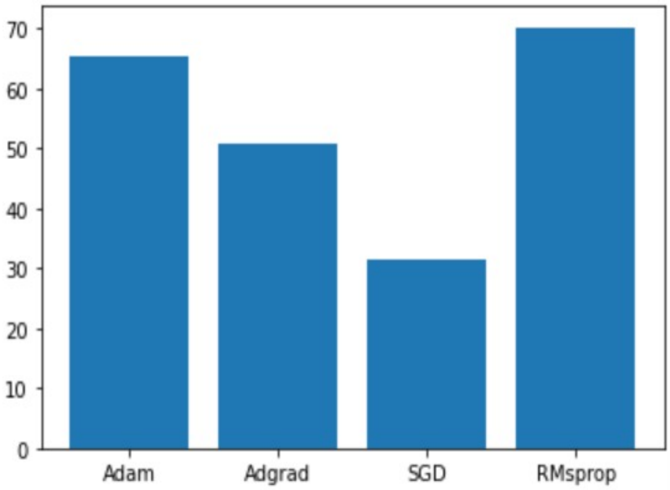

Figure 5: Impact of Optimizers in Deep Learning

Figure 5 shows the impact of different optimizers in deep learning model. According to analysis, the best optimizer is RMSprop, which provides accuracy of 70.156% whereas Adam, Adagrad, and SMD give the accuracy of 60.156 %, 50.625% and 31.406 % respectively.

Table 1 represents confusion matrix for deep learning with three data labels negative, neutral and positive. Table 2 represents the performance metrics for the deep learning model. The weighted average precision is 69%, weighted average recall is 65% and weighted average f1-score is 66%.

Table 1: Confusion Matrix for Deep Learning

	Predicted Negative	**Predicted Neutral**	**Predicted Positive**
Actual Negative	150	4	47
Actual Neutral	0	129	102
Actual Positive	34	36	138

Table 2: Performance Metrics for Deep Learning

Data Label	precision	recall	f1- score	support
Negative	0.82	0.75	0.78	201
Neutral	0.76	0.56	0.65	231
Positive	0.48	0.66	0.56	208
Weighted Average	0.69	0.65	0.66	640

D. Performance Analysis of Recurrent Neural Network

In this model a Recurrent Neural Network (RNN) with Gated Recurrent Unit (GRU) is used. Figure 6 shows the impact of epochs in Recurrent Neural Network Model. The model is trained at different numbers of epochs 50, 80, 100, 130, and 150 after selecting the batch size 32, and Adam Optimizer. Figure shows that model achieved the highest accuracy is 97 at 100 epochs.

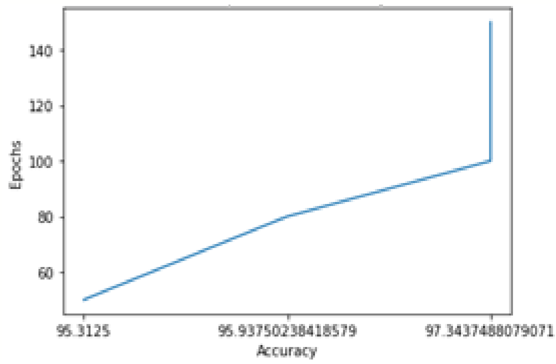

Figure 6: Impact of Epochs in Recurrent Neural Network

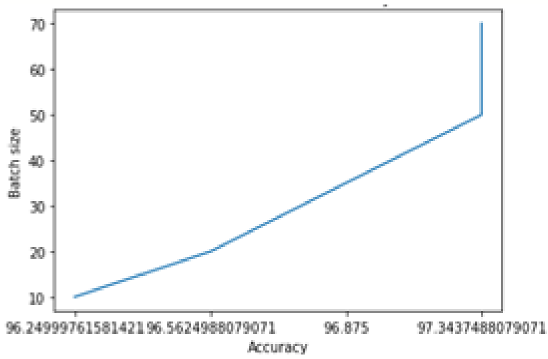

Figure 7: Impact of Batch Size in Recurrent Neural Network

Figure 7 represent the impact of batch size in Recurrent Neural Network Model. The model is trained at different batch size 10, 20, 35, 50, and 70 after selecting the epoch 150, and Adam Optimizer. It is clear from the figure the accuracy of model increases as the batch size increases. Figure shows that model achieved the highest accuracy at 50 batch size.

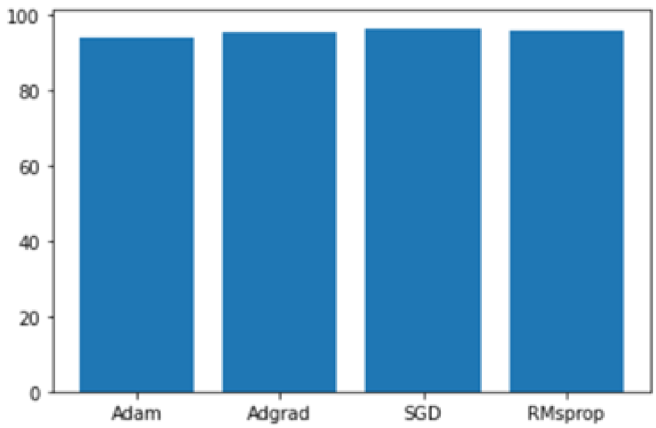

Figure 8: Impact of Optimizers in Recurrent Neural Network

Figure 8 shows the impact of different optimizers i Recurrent Neural Network Model. According to analysis, the best optimizer is SGD, which provides accuracy of 96.528% whereas Adam, Adagrad, and RMSprop give the accuracy of 94.219 %, 95.469% and 96.094 % respectively.

Table 3 represents confusion matrix for Recurrent Neural Network Model three data labels negative, neutral and positive. Table 4 represents the performance metrics for the Recurrent Neural Network Model. The weighted average precision is 97%, weighted average recall is 97% and weighted average f1-score is 99%.

Table 3: Confusion Matrix for Recurrent Neural Network

	Predicted Negative	Predicted Neutral	Predicted Positive
Actual Negative	197	0	4
Actual Neutral	0	224	7
Actual Positive	8	3	197

Table 4: Performance Metrics for Recurrent Neural Network

Data Label	precision	recall	f1- score	support
Negative	0.96	0.98	0.97	201
Neutral	0.99	0.97	0.98	231
Positive	0.95	0.95	0.95	208
Weighted Average	0.97	0.97	0.99	640

The recurrent neural network model outperformed the deep learning model in the experiments, as seen above. In comparison to the recurrent neural network model, the deep learning model has lower precision, recall, and f2-score.

VI. CONCLUSION AND FUTURE WORK

In this paper, we used two models, Deep Learning and RNN with GRU, to undertake experiments on an EEG brainwave dataset. Our system has yielded recognition accuracy of 97.343% by using recurrent neural network model with gated recurrent unit which is better than recognition rate of current system. Our findings revealed that, unlike image processing, emotion identification using EEG signals necessitates a multidisciplinary approach that includes neuroscience, engineering, computer science, and psychology. Going further than the recent performance of emotion detection algorithms, however, will require more research in neuroscience and psychology, or the use of a multi-modal method that blends EEG-based emotion identification models with image processing-based techniques.

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