Emotion Type Recognition Scheme Using EEG Based Signals

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***Abstract*—Due to the increased usage of metaverse platforms and the introduction of digital humans, emotions are one of the main keys to help the digital human assist the user. Certain emotions have been produced on intentionally in order to study how emotions impact decision-making. The objective is to enhance the ability to recognize human expressions when training artificial intelligence models. However, some people have difficulties in producing and percieving emotions. This paper will present a GRU based model to classify the type of emotion the user is feeling. The proposed solution shows better accuracy as well as less loss than the existing works.**

***Index Terms*—EEG Signal, Emotion Recognition, Autism Spectrum Disorder, Deep Learning, classification.**

I. Introduction

Due to the substantial breakthroughs in this field, the Metaverse is presently experiencing a rapid growth in usage every day, which has sparked the attention of many people in visiting this realm. [1]. The creation of artificially intelligent, autonomously animating, and animated virtual people known as "digital humans" is being facilitated by contemporary technology [2]. In that sense, the importance of emotions in decision-making has gained increased attention during the past few decades. Some emotions have been purposely created to investigate how emotions impact decision-making [3]. However, some people have hard difficulties in producing and precieving emotional facial expressions [4], autistics are no exception [4].

In this study [5], they showed how a deep learning approach can simultaneously learn the characteristics of the EEG data and identify its emotions. Their method is distinctive in that deep learning was applied to the raw data without the requirement for human feature extraction, and that three layers of constrained Boltz-mann machines were used (RBMs). Despite the fact that there were only a few epochs available for each participant since the EEG data is subject-specific, they still trained their emotion model subject-by-subject. The results of the studies demonstrate that subject dependency exists for EEG signal emotion identification, and their implementation of subject-tied deep learning beat more conventional algorithms in terms of recognition accuracy.

The objective of this study is to develop a deep learning model that can recognize user emotions using EEG signal data from individuals. The emotions will be classified as neutral, positive and negative emotions according the brain signal readings. Additionally, the results of the emotional-EEG signal recognition will be compared to different existing work.

II. System design/ Methodology

The suggested model is shown in Figure 1. We will start by reading the user's EEG signal. The input will be provided to the AI model after being scaled and filtered. At this stage, the AI model will function and start categorizing the emotion types based on the gathered dataset. The module will be used to extract the type of emotion from it, whether it is neutral, positive, or negative.

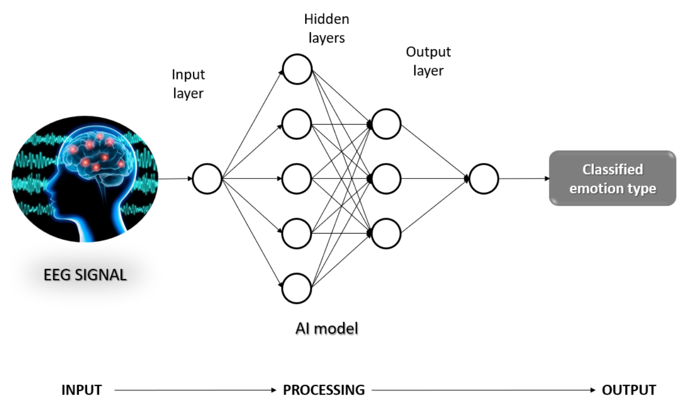

Fig. 1. Proposed logic flow chart

A. Dataset Description

The dataset that has been used for model is publicly available and it was collected from two people—a male and a female—over the course of three minutes in each of the three states—positive, neutral, and negative. An EEG headgear was utilized to record the TP9, AF7, AF8, and TP10 EEG placements using dry electrodes [6].

B. Proposed Methodology

The model's paramters is built using Python code in google colab which is shown in table I. There are 502,083 total parameters, which is the same number as trainable parameters. When implemented, this model operates in a categorical manner. There was an input layer consisting of (none, 2548), followed by the TFOpLambda function. Following that, we utilized Keras layers Gated recurrent unit (GRU) with 64 neurons and the return sequence True. The result is then flattened using the dense function and softmax activation method after applying the flatten function. Lastly, Adam serves as our optimizer to obtain model correctness and categorical crossentropy was used to calculate the model loss.

TABLE I
PROPOSED SYSTEM PARAMETERS

Layer (type)	Output Shape	Parameters
input_1 (InputLayer)	(None,2548)	0
tf.expand_dims(TFOpLambda)	(None, 2548, 1)	0
gru (GRU)	(None, 2548, 64)	12864
flatten (FLATTEN)	(None,163072)	0
dense (DENSE)	(None,3)	489219

III. Result discussion

The accuracy and loss of the model is depicted in Figure 2 and figure 3 respectively. To validate the outcomes and provide their classification reports, we trained several classifiers on the dataset, such as SVC, Logistic Regression, Decision Tree Regressor and Random Forest Classifier. For the performance metrics, all classifiers nearly produce the same results. The average accuracy achieved in this model from precision, recall and f1-score was approximately 97%. In addition, the loss on testing was roughly 0.1221.

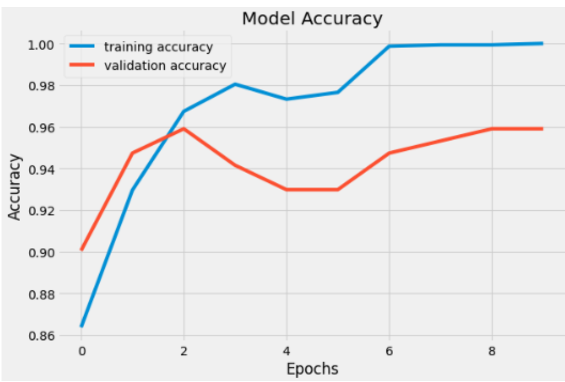

Fig. 2. Model Accuracy

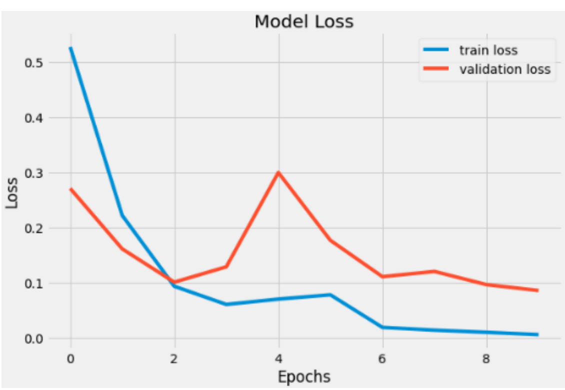

Fig. 3. Model Loss

According to table II, it can be clearly seen that our model had shown better results for accuracy compared to the mentioned existing works. In addition, the use of GRU model with 64 neurons gave satisfactory results with relatively short training time compared to using 128 or 256 neurons.

TABLE II
RESULT COMPARISON

Model	Our model	[7]	[5]	[8]
Accuracy	96.95%	90.0%	60.8	85.17%

IV. Conclusion

Emotions are key factors to understand humans better and provide them with better services, digital humans are no exception to this since they need to be trained with high precision to able to function well serving Metaverse and internet users . In this work we developed a neural network that can classify emotions that is read from EEG signal to three classes; Neutral, Positive and Negative. Our model was effective in achieving an accuracy of 96.95%, making it the most accurate among the papers cited. However, the model can classify the type of emotion, not specifically what emotion it is. Future work will include enhancing the emotion recognition by integrating speech-emotional recognition (SER) to our model as well as minimizing the model loss.

V. ACKNOWLEDGMENT

This work was supported by NRF-2022R1I1A1A010701058 as well as Priority Research Centers Program through the National Research Foundation of Korea(NRF) funded by the Ministry of Education, Science and Technology(MEST)(2018R1A6A1A03024003). It was also supported by the MSIT(Ministry of Science and ICT), Korea, under the Grand Information Technology Research Center support program(IITP-2023-2020-0-01612) supervised by the IITP(Institute for Information communications Technology Planning Evaluation)

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