Gender based Emotion Classification using M-GRU based on Brain EEG Signal

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Abstract— The need for computer programs that can identify a user's present emotional state is increasing all the time. Research on identifying emotion from the face and voice has previously been done in an attempt to mimic human communication. Humans can discern emotions with 70-98 percent accuracy from these signals, and computers are already fairly good at classifying facial expressions (80-90 percent). These programs train the brain's response by using information about the test subject's mental or emotional state. Computational models called neural networks are modeled after the structure and operation of the human brain. They have artificial neurons that are interconnected, arranged in layers, and are able to learn and make decisions depending on input data. For this study, one male and one female volunteer were chosen. Our findings suggest that brain EEG waves can be used to detect emotions. Cortical activity is reconstructed with high resolution and spatiotemporal precision using the new multi-mode EEG/MRI integrated approach. A new application of BCI proposed in this research is the prediction of emotion based on a person's gender using EEG analysis using Modified Gated Recurrent Unit (M-GRU). The accuracy of emotion recognition based on gender classification difficulties was 95.312 percent.

Keywords— MRI, EEG, RNN, Brain-computer interaction, M-GRU, LSTM

I. INTRODUCTION

The brain generates brain waves while transmitting messages. Brain wave data is a type of biological signal often associated with emotion. [1] Emotion features can be extracted from brain wave transmissions through analysis. However, human emotion complexity arises from environmental background and cultural diversity. Therefore, the classification method is crucial in brain wave emotion analysis.

Recent breakthroughs in natural language processing, image classification, video tracking, and speech sequence modelling have shown great success for deep learning models like Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks. These models are excellent in learning complex feature representations without the need for significant feature engineering, as they inherently possess end-to-end self-learning capabilities.

Currently, CNN, RNN, and LSTM are currently being investigated to describe EEG signals, with research still in its infancy. Classifying forms of emotion remains the biggest challenge when trying to analyse the brain waves relating to emotions. However, since Brain Potter is one-of-a-kind and unique, he cannot differentiate between the 22 different varieties of emotions amongst humans.

Brain Wave Emotion categorization can classify emotion types into six fundamental emotions: happiness, anger, fear, surprise, sadness, and disgust. [26] Psychologists provide the following insights on basic emotions:

Fear: A natural response of a species or individual in a life-threatening situation. Its symptoms include an irregular heart rate, high blood pressure, and night sweats; Anger: Emotional irritation stemming from feelings of being violated, abused, or treated unfairly; Sadness: Generally a bad mood that stems from psychological failure; Happiness: A pleasurable psychological condition which is experienced by the emotions of happiness, glory, and expectations; Surprise: Short stopping of actions as a consequence of stimulation from the living environment; Disgust: Response as a consequence of exposure to unwelcome feelings within the surrounding.

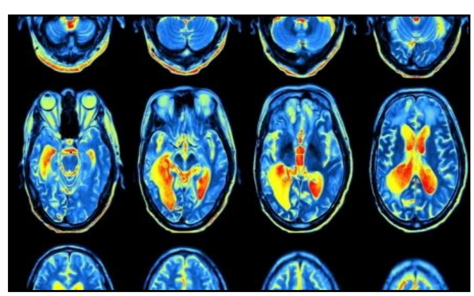


Fig. 1. Example of a figure caption.

II. Literature Survey

EEG signals are a non-invasive means of obtaining emotions from disabled individuals using EEG headsets. [3] We propose deep learning methods to analyse EEG signals and classify emotions simultaneously. This is in contrast to the traditional methods applied directly to raw signals without explicit feature extraction. Because EEG signals are subject-dependent, training emotion models subject-wise proves to be effective even with limited data per subject.[27] Automatic speaker gender identification has various applications. Gender-dependent models are superior to gender-independent models in speech recognition. AGR aims to find a person's gender from voice or audio information. AGR findings can be applied in several applications, including creating gender-specific speech models, reducing research for speaker/voice recognition, and analysing human-computer interaction and social behaviour.Neural networks formed the basis for early computer vision gender recognition systems. [4] Golomb et al. used facial images to create SEXNET, a fully connected network with two layers for gender recognition. Pronobis et al. [5] studied fundamental frequency (F0) and cepstral features of speech. They used the BANACA corpus dataset for their experiments. Jian-Gang et al. [6] proposed score-level fusion with Adaboost for speaker gender identification. They showed that their approach was better than using only voice data. Yi-jie Zhao et al. [7] presented gender recognition using over 80% accuracy with a method based on colour information. Mehmet et al. [8] analysed perceptual audio features in emotion recognition. They proposed acoustic features to draw emotional information from audio. Carlos et al. [9] analyzed the visually salient aspect of the fundamental frequency in terms of emotionally recognizing the individual. David Philippou-hubner et al. [10] studied the effect of speaking rate in emotion recognition from speech signals, as speaking rate is easily perceived and an important prosodic feature of speech. Et al. [11] focused on two-way categorization. They studied pitch, MFCCs, and formants, showing that features from agitated emotions share similarities. Dipti D. Joshi et al. [12] discussed some feature extraction and classification techniques; they summarized some of the latest research in speech emotion recognition. Electrodes recorded EEG signals. [14] EEG channels and two reference channels allowed for high spatial resolution. The data was obtained from a male and a female participant. The films were used to stimulate their brains to give the brain signals. [15] Results were discussed based on the objective of the experiment. Participants were shown various films (sad, happy, normal, horror, etc.) at different times. Signals were then collected using the electrodes. Analysis revealed that female vocal cords are generally thinner and shorter than males. Also, a woman's voice often has a higher fundamental frequency. Therefore, fundamental frequency is a suitable feature for gender identification. Pitch, energy, and speaking rate are crucial features to extract from audio for emotion identification. One can quickly determine a person's emotion by observing their voice's pitch, speaking rate, and energy. For example, speech during fear, anger, or excitement increases in speed, volume, clarity, and frequency variation.

III. Proposed Methodology

For this research, we used a Kaggle dataset called emotions.csv. [2] For this dataset, information is gathered from two individuals (a man and a female) for a total of three minutes for each mood (positive, neutral, and negative). The TP9, AF7, AF8, and TP10 EEG placements were then recorded using a muse EEG headband, which utilized dry electrodes. The purpose here is to determine the impact of emotion on brain waves.To build a M-GRU for gender-based emotion classification, we have proposed this structure:

- Input Layer: It receives the features related to emotion classification. These features is including text data, facial expression data, voice recordings, or any other relevant information.
- Preprocessing: This layer is performing necessary preprocessing steps on the input data that are tokenization, normalization, and feature extraction. This step will depend on the specific data types and characteristics.
- Hidden Layers: Between the input and yield layers, include one or more covered up layers. Depending on how difficult the issue is, the number of covered up layers and the number of neurons in each layer are altered.
- Activation Functions: Apply activation functions to the outputs of neurons in the hidden layers to introduce non-linearity. ELU (Exponential Linear Unit) is a variant of ReLU that handles negative inputs more gracefully so we have used these as a activation function. It smoothly maps negative inputs to negative values instead of zero. For positive inputs, it acts like ReLU.

$$ELU(v) = v \; if \; v >= 0, and \; ELU(v) = alpha \; (exp(v) - 1) \; if \; v < 0$$

  Where, alpha is considered as a small +ve constant. ELU can alleviate the dying ReLU problem and has been shown to improve learning performance in some cases.

- Output Layer: In gender-based emotion classification, the output layer would typically have two neurons, representing male and female emotions. In the context of gender-based classification, where the goal is to predict the gender (male or female) based on input features, the softmax activation function can be applied to the output layer of the neural network.
- Connections and Weights: Neurons in each layer are associated to neurons within the ensuing layer. Each association has an related weight, which is balanced amid preparing to optimize the network's execution.
- Training and Optimization: Prepare the neural arrange utilizing labelled information, where the input highlights are related with the comparing gender-based feeling names. Utilize optimization calculations such as stochastic slope plunge (SGD) or Adam to upgrade the network's weights and predispositions.

- Evaluation: Assess the prepared demonstrate employing a isolated approval or test dataset to evaluate its execution. Common assessment measurements incorporate precision, accuracy, review, and F1 score.

The dataset employed in this approach would be used to accurately detect emotion. We'll see if this holds true as the project progresses. Feelings are state of intellect activated by neurophysiologic changes and are connected to considerations, sensations, behavioral reactions and a level of delight or disappointment. There's no logical understanding on a definition at this time. Temperament, disposition, identity, and innovativeness are all related with feelings.[16] A gated repetitive unit may be a sort of repetitive neural network that employments associations between hubs to achieve machine-learning errands such as memory and clustering in discourse acknowledgment, for example.Now, we've got a dataset of two people, A and B, who each had varied brain EEG signals at different times while watching films of different emotion genres and emotions. We then plotted them in different graphs and compared them using matplotlib [17]. After that, we trained 70% of the data and tested the remaining 30%. The data was then represented as a GRU (Gated Recurrent Unit), which remembers the pattern of emotions over time. This aids in improving the prediction's accuracy. Finally, we plotted a resulting graph using a confusion matrix, and the accuracy was 95.312 percent [18]. M-GRU works by storing simultaneous past feelings in nodes, which minimizes the complexity of human emotions. This improves the accuracy from 52.12 percent to 95.312 percent. Thus, the basic emotions of human (fear, anger, happiness, sad, disgust, surprise) can be easily classified from our model.[25]

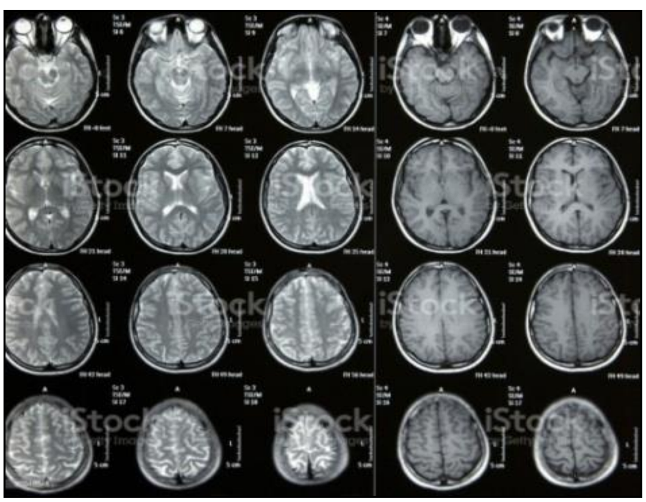


Fig. 2. Scan of Cerebrum.

IV. Result and Analysis

A. *Algorithm:*

- STEP 1: Import, Numpy, Pandas, Matplotlib, Seaborn, Tensorflow, Keras and Scikitlearn.
- STEP 2: Read the dataset for the project using pandas and print it.
- STEP 3: From dataset consider signals for person A from timestab 0 to timestab 749 of any serial number (fft_0_a-fft_749_a). Plot this in a graph where x axis is range of the length of sample and y axis is sample.
- STEP 4: Repeat the STEP 3 for timestab “fft_0_b-fft_749_b”.
- STEP 5: Replace the label column for preprocessing the dataframe. Using train_test_split, train 70% of the dataframe and skip 30% for testing.
- STEP 6: Use [19] GRU (Gated Recurrent Unit) for modelling the dataframe. The layers, GRU and Flatten models for the output layers.
- STEP 7: Convert the dataframe into accuracy metrics then train the model upto 50 epochs.
- STEP 8: Evaluate the test accuracy upto 3 significant places.
- STEP 9: Use the model to print confusion metrics for Y_{test} and Y_{pred} . Finally print the classification report.[22]

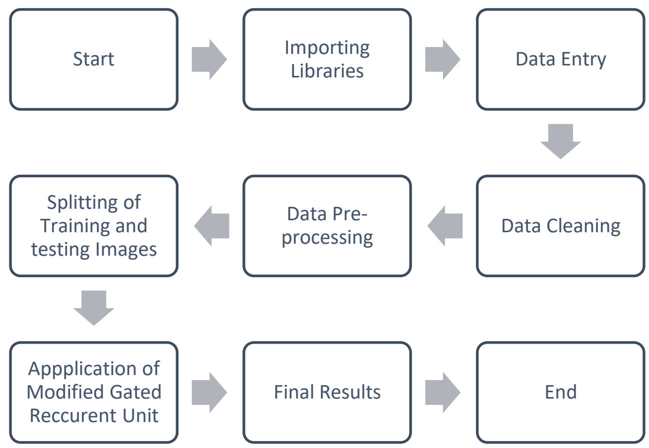


Fig. 3. Flow Chart

The equations for a M-GRU unit can be summarized as follows:
The sigmoid activation function maps the input values to the range of [0, 1]. It has an S-shaped curve and is given by the formula,

$$Sigmoid\ (x) = 1 / (1 + exp(-x))$$

$$Update\ Gate\ (z){:}\ z = sigmoid\ \left(W_z * \left[x, h_{prev}\right]\right)$$

$$ResetGate\ (r){:}\ r = sigmoid\left(W_r * \left[x, h_{prev}\right]\right)$$

$$Candidate\ Hidden\ State\ ({\sim}h){:}\ {\sim}h = tanh\left(W_h * \left[x, r * h_{prev}\right]\right)$$

$$Hidden\ State\ (h){:}\ h = (1 - z) * h_{prev} + z * {\sim}h$$

In these equations, x represents the input at the current time step, h_{prev} is the previous hidden state, and $[\mathrm{x}, \mathrm{h}_{\mathrm{prev}}]$denotes the concatenation of the input and the previous hidden state, $W_z W_r$ and W_h are learnable weight matrices associated with the input, reset gate, and candidate-hidden state, respectively.

B. *Output:*

Given an input vector $b = [b_1, b_2]$, where b_1 and b_2 represent the logits or outputs of the network for male and female genders respectively, the softmax activation function produces a probability distribution:

$$softmax(b) = [\ (exp(b1)) / (\frac{(exp(b1) + exp(b2)), exp(b2)}{((exp(b1) + exp(b2))})]$$

The softmax work exponentiates the logits and normalizes them by partitioning each exponentiated esteem by the entirety of all exponentiated values. This guarantees that the coming about values lie between and 1 and whole up to 1, speaking to a substantial likelihood dispersion.

The output of the softmax function can be interpreted as the predicted probabilities of the classes.

- Plotting of EEG Graph: Data was collected from two people where muse EEG headband was used to record brain signals via dry electrodes. We plotted it using matplotlib to get the required EEG signal for male (Fig. 4) and for female (Fig. 5).

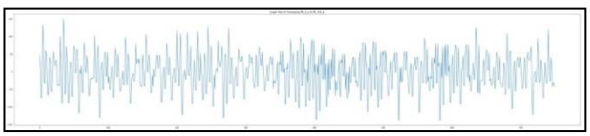


Fig. 4. EEG of male participant

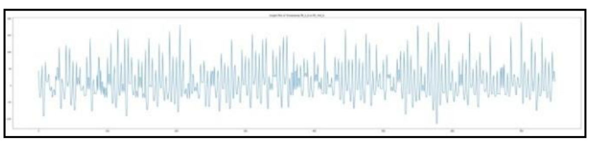


Fig. 5. EEG of female participant

- Training the Dataset: We have trained 70% of the data and kept 30% for testing.

```
NEUTRAL     716
NEGATIVE    708
POSITIVE    708
Name: label, dtype: int64
```

Fig. 6. Neutral, Negative and positive values

	# mean_0_a	mean_1_a	mean_2_a	mean_3_a	mean_4_a	mean_d_0_a	mean_d_1_a	mean_d_2_a	mean_d_3_a	mean_d_4_a	...	fft_740_b	fft_741_b	fft_742_b	fft_743_b	fft_744_b	fft_745_b	fft_746_b	fft_747_b	fft_748_b	fft_749_b
952	27.20	29.7	30.10	25.10	25.6	-2.470	-2.3100	-2.910	0.401	-0.590	...	128.0	25.60	-22.90	-22.90	25.60	106.0	24.0000	-9.58	-9.58	24.0000
735	31.50	31.6	31.30	28.90	27.4	-4.290	1.8000	-1.290	-4.070	-1.550	...	108.0	-10.50	19.40	19.40	-10.50	91.0	-16.3000	21.10	21.10	-16.3000
799	10.60	29.3	186.00	21.30	23.1	1.150	2.2300	-34.000	0.593	-2.790	...	285.0	-51.50	1.26	1.26	-51.50	425.0	-262.0000	99.10	99.10	-262.0000
1189	28.80	32.9	41.40	27.10	24.8	-2.680	0.2980	7.800	-3.510	2.910	...	116.0	-7.74	5.90	5.90	-7.74	185.0	0.0392	-19.50	-19.50	0.0392
772	31.00	33.5	24.50	28.50	24.0	-9.230	-6.2000	7.500	-5.130	-0.540	...	126.0	-5.53	34.90	34.90	-5.53	109.0	-36.5000	55.90	55.90	-36.5000
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2009	7.22	25.5	-332.00	6.27	29.4	-0.977	-0.0737	0.509	-1.570	4.000	...	-163.0	256.00	-63.80	-63.80	256.00	-137.0	154.0000	-69.40	-69.40	154.0000
1180	28.80	28.5	76.80	31.10	25.4	16.200	4.4800	78.300	11.200	0.396	...	103.0	27.40	17.90	17.90	27.40	91.7	30.1000	12.10	12.10	30.1000
1344	12.90	22.4	-3.34	7.96	27.1	-10.800	0.7210	49.500	-5.170	-0.425	...	70.3	15.00	-58.30	-58.30	15.00	97.9	33.7000	10.40	10.40	33.7000
527	27.70	32.0	30.70	26.10	27.3	-7.270	1.6100	-0.851	-8.000	13.800	...	39.9	-54.70	31.10	31.10	-54.70	33.6	-1.3300	-47.60	-47.60	-1.3300
1289	14.10	32.0	-173.00	22.50	24.0	2.560	-1.8500	67.300	3.660	-0.867	...	73.8	115.00	-125.00	-125.00	115.00	460.0	-194.0000	75.70	75.70	-194.0000

492 rows × 2548 columns

Fig. 7. Testing Result of Dataset

- Modelling of the Dataset: GRU has two gates, that are reset and update, while LSTM has three gates: input, output and forget. In order to consider human emotions, we used M-GRU because it is required to remember the previous emotions for an accurate prediction. Thus in modelling we used M-GRU instead of any other layer.

- Accuracy Matrix and Epoch: We have made 50 epochs for our dataset. Due to these 50 numbers of passes and the M-GRU modelling, the accuracy of the prediction increases to 95.312%. Results as depicted from figure 4-10.

- Confusion Matrix: The figure 11 plots the false positive to the true negative for the dataset. The four phases are: false positive, false negative, true positive, true negative

```
Model: "functional_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_2 (InputLayer)         [(None, 2548)]            0
_________________________________________________________________
tf_op_layer_ExpandDims_1 (Te [(None, 2548, 1)]         0
_________________________________________________________________
gru_1 (GRU)                  (None, 2548, 256)         198912
_________________________________________________________________
flatten_1 (Flatten)          (None, 652288)            0
_________________________________________________________________
dense_1 (Dense)              (None, 3)                 1956867
=================================================================
Total params: 2,155,779
Trainable params: 2,155,779
Non-trainable params: 0
_________________________________________________________________
None
```

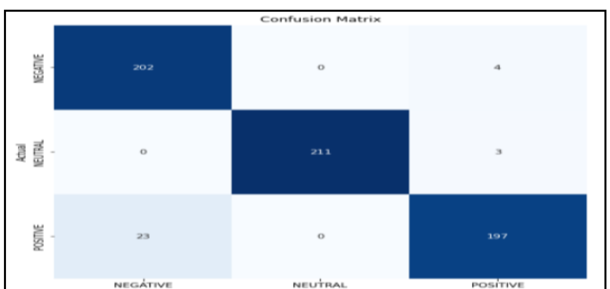
Fig. 8. Modelling of the dataset

```
Test Accuracy:  95.312%
```

Fig. 9. Testing Accuracy Score

```
Epoch 1/50
38/38 [==============================] - 888s 23s/step - loss: 33.5923 - accuracy: 0.7863 - val_loss: 10.2756 - val_accuracy: 0.8696
Epoch 2/50
38/38 [==============================] - 923s 24s/step - loss: 5.5126 - accuracy: 0.9187 - val_loss: 8.3568 - val_accuracy: 0.8997
Epoch 3/50
38/38 [==============================] - 915s 24s/step - loss: 3.8419 - accuracy: 0.9355 - val_loss: 3.9908 - val_accuracy: 0.9431
Epoch 4/50
38/38 [==============================] - 1048s 28s/step - loss: 0.5558 - accuracy: 0.9832 - val_loss: 3.6235 - val_accuracy: 0.9431
Epoch 5/50
38/38 [==============================] - 1197s 31s/step - loss: 1.3961 - accuracy: 0.9673 - val_loss: 4.5190 - val_accuracy: 0.9231
Epoch 6/50
38/38 [==============================] - 1123s 30s/step - loss: 0.3669 - accuracy: 0.9883 - val_loss: 6.9430 - val_accuracy: 0.9064
Epoch 7/50
38/38 [==============================] - 1057s 28s/step - loss: 0.5389 - accuracy: 0.9858 - val_loss: 6.9648 - val_accuracy: 0.9231
Epoch 8/50
38/38 [==============================] - 967s 25s/step - loss: 1.4581 - accuracy: 0.9732 - val_loss: 6.1688 - val_accuracy: 0.9231
Epoch 9/50
38/38 [==============================] - 986s 26s/step - loss: 0.4397 - accuracy: 0.9883 - val_loss: 9.4753 - val_accuracy: 0.9197
```

Fig. 10. Testing Accuracy Result




```
Classification Report:
----------------------
              precision    recall  f1-score   support

    NEGATIVE       0.90      0.98      0.94       206
     NEUTRAL       1.00      0.99      0.99       214
    POSITIVE       0.97      0.90      0.93       220

    accuracy                           0.95       640
   macro avg       0.95      0.95      0.95       640
weighted avg       0.96      0.95      0.95       640
```

Fig. 11. Confusion Matrix and Classification Report

V. Conclusion and Future Scope

Emotion recognition is important to enhance human computer interaction. [23] EEG is non-invasive because the signals are extracted from the scalp. Electrode placement is a source of noise. [24] Object recognition and removal is a major challenge for engineers. The proposed method is suitable for EEG signals with high variability, thus enabling accurate recording of emotions and identification of feature vectors. This approach identifies short-duration EEG signals and pinpoints human emotions effectively. We tried the first models with Dense and Flatten layers and achieved an accuracy of 57%. Next, we applied M-GRU, which controls the data flow through the gates and a hidden state. M-GRU overcomes the RNN problems by having two gates: update and reset gates. LSTM contains three gates: input, forget, and output. [20] [21] GRU does not have an output gate and combines input and forget gates into a single update gate. GRU shares a lot of its features with LSTM. It regulates the memorization process through a gating mechanism. Utilizing this approach, we obtained 95.312% accuracy. Our approach correctly evaluates individual emotional variations to predict personality traits. We can classify correctly into two classes of each of the personality trait dimension based solely upon brainwave dynamics. The above analysis is indicative of emotional accuracy differences as a function of gender and males outperform females in this activity.

Women sometimes express two different emotions similarly, reacting the same way in different situations. For instance, they may shout loudly in both happy and sad moods. Males, on the other hand, usually react differently, expressing emotions uniquely. This makes it easier to identify a man's emotions.[13] Future research could combine recordings of a user's brain processes in response to emotional stimuli with their social media digital footprints to infer personality. This method can be applied to AI-curated devices such as Alexa and Google Home. Our framework has led to a high-performance system for personality inference by analyzing the brainwaves of an individual in response to emotional film clips

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