Human Emotion Identification Using Brain Waves and Facial Images

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Abstract. Emotions carry considerable weight in any human interaction. This study presents a bimodal framework for detecting emotions through which brainwaves are combined with facial images to promote better identification of emotions. The EEG data sets acquired non-invasively resolve internal neuronal activities across frequency bands manifesting an emotional state. Simultaneously, the facial expressions including happiness, sadness, and neutrality provide an inhibitory complementary layer of observation. The merging of these two methodologies delivers more fine-tuned knowledge into the subject of emotion as such observations can greatly help in cases of stress management and supporting people who have an impaired ability to communicate.

1 Introduction

Electroencephalography (EEG) is a non-invasive technique that is used for monitoring the brain activity, by placing the electrodes on the scalp for recording electrical signals from the brain. These signals reflect cognitive and emotional states through various frequency bands. Delta waves indicate deep sleep, Theta is linked with drowsiness, Alpha reflects calmness, Beta relates to alertness and active thinking, and Gamma corresponds with higher-level cognitive processing. Understanding these patterns is essential for assessing internal emotional states, especially when outward facial expressions may be ambiguous or misleading. The electrodes may be dry or wet electrodes depending on the devices, these will be placed on the scalp of the head for collecting the non-invasive EEG signals. These electrical signals are produced due to the voltage variation that are being monitored using the EEG device.

The different range of frequency of brain waves are being generated based on the mental state of the brain. These EEG signals are being classified into 6 types based on their frequency levels. Delta waves are the slowest brain wave whose frequency range is of 0.5Hz to 4Hz. The next waves are the Theta waves, which are being observed during the drowsiness state. By using a specific computational method, we can record the raw EEG signal. The third wave is the Theta waves. Its

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frequencyranges from 4Hz to 8Hz. Then comes the Alpha waves, which can be observed only when the brain is in relaxed state. It has a frequency range from 8Hz to 12Hz. The waves that are generated only during the high alert mode of brain are known as Beta waves. It is completely focusses on mental activities such as attentive, decision making, problem solving and so on. It possess fast activity, present in brain only during alert stage of a human. The final fastest brain waves with high frequency are the Gamma waves with its frequency range from 38 to42Hz. These waves are known for simultaneous processing of information that this being received from the brain. The usual Mu range is between 8-13Hz which partly overlaps with other frequencies. It reflects the synchronous firing of motor neurons which is in the rest state. The classifications of brain waves is given in the Figure1.

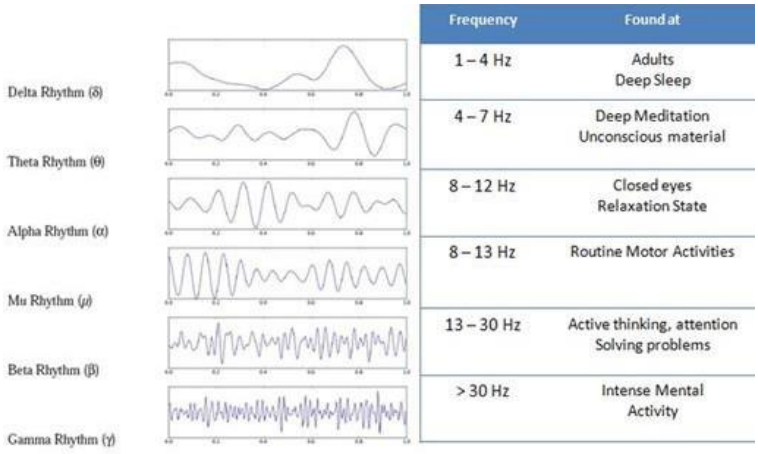

Fig. 1: Classification of human brainwave frequency bands

2 Process Flow

With regards to identifying human emotions, it constitutes something that is vital to communication and interaction among people. Emotions constitute rather complicated and quite subjective experiences manifested onto some types of expressions, be that through facial expressions, body movements, or speech. In recent years, advanced technologies are used to identify and analyze human emotions. Two such technologies are brainwave and facial image analysis. Brainwave analysis involves measuring the electrical activity in the brain using an electroencephalogram (EEG) to identify patterns associated with different emotional states The algorithmic computer vision identifies and interprets human emotions through facial analytics: happiness, sadness, anger, surprise. The sciences are said to enhance one another, offering arguably more precision in the recognition of emotion. With brainwaves being matched with image data, an accomplished researcher could identify the gist of an individual's emotional state, which finds significance across several applications, such as the diagnosis of mental health, market research, and the design of human-computer interaction experiences. However, the existence of these technologies also retains ethical considerations in regard to potential invasions of privacy, or outright misuse of such tools. It is, thus, pertinent to reflect upon the consequences and limitations that these technologies pose before instilling them in practical application. Hence it is important to carefully consider the implications and limitations of these technologies before implementing them in real-world scenarios.

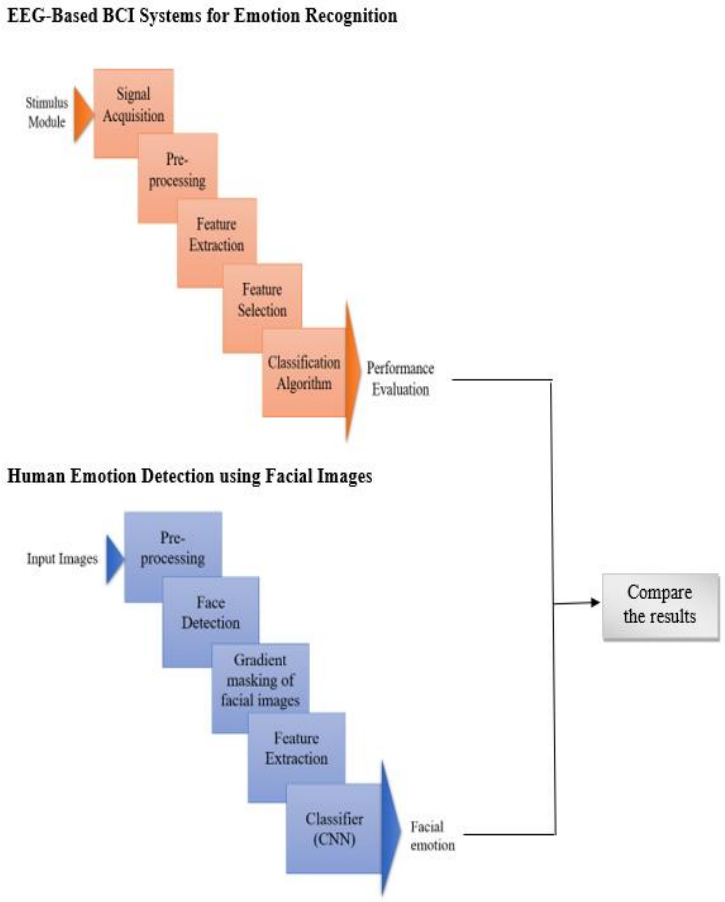

Fig. 2: Overall process flow of the proposed multimodal emotion-recognition system

This system uses software for its analysis. It is a combined method of brainwaves and facial images. EEG-Based BCI Systems is essentially detecting emotion through brain activity analysis. The data are first taken, then preprocessing is carried out, features are extracted and selected by classification algorithms, and the results are observed in the concluding matrix. Human Emotion Identification with Facial Images is the analysis of emotions using facial images. Today, the dataset is collected, which serves as input; the images are preprocessed, features are extracted, and finally fed into a CNN model. Both analyses are then compared to decide on human emotions.

3 Literature Survey

Human emotion identification using brain waves and facial images is an active area of research that falls under the field of affective computing. Affective computing involves the development of technology that can recognize, interpret, and respond to human emotions. Emotion Recognition has been identified as the key technological aspects in human lives. It also has grown as an important technology in the Human Computer Interaction field with an automation methodology to improve EEG signals in real time monitoring that reacts to emotional changes. The computational processes mentioned comprise of the general methodology for EEG-based BCI emotion recognition. The various machine and deep learning classification techniques and commonly used performance metrics [1]. This article presents a novel approach for emotion recognition using EEG signals and facial images. It uses a multimodal deep learning model to extract features from both brain signals and facial images and achieves

high accuracy in emotion recognition [2]. The different algorithms and processes that can be part of EEG-based BCI emotion recognition systems: (1) Emotion elicitation, (2) signal acquisition, (3) feature extraction and selection, (4) classification techniques, and (5) performance evaluation. In fact, as per the review, computational methods do not observe standards for varied applications; the researchers keep on searching for solutions in the interminable quest. The study on the relation of brain signals with emotions is another complex problem with newer methods and newer implementations always being presented [3]. This review article overviews various approaches and techniques for emotion recognition using brain signals. It discusses the use of EEG, fMRI, and other imaging techniques to detect emotions [4]. This review article overviews various approaches and techniques used for emotion recognition-from brain signals. It discusses the use of EEG, fMRI, and other imaging techniques for detecting emotions [5]."An emotion can be a positive or negative experience that is being associated with a pattern of physiological activity. Then, an improved wavelet-based feature extraction algorithm is proposed. Further this algorithm is tested for different classifiers namely k Nearest Neighbor (KNN), Quadratic Discriminant Analysis (QDA), Support Vector Machine (SVM) Linear Discriminant Analysis (LDA). The average sensitivity obtained for the present work was 92.97% with an accuracy of 91.67%, which is better result than the previous work [6].This paper proposes a deep learning-based approach for emotion recognition on small datasets, using transfer learning to leverage pretrained models [7].

4 Methodology

Like in anything related to autism, identifying the emotions can be quite difficult. Facial expressions, speech, behaviors (either gestures or postures), and physiological signals are all ways to detect and identify human emotions.

From the signals both psychological and facial expressions, the emotions of a particular individual are being "tagged." The facial expressions or images are used for that purpose. This can lead to possible downside when relying solely upon facial-image-based systems or facial recognition technologies- environmental aspects, social or cultural norms, and peculiarities induced by facial development of the individual can influence facial expressions. Up to psychological origin, EEG signals are the way to go. These are real-time responsive signals and show more subtle variation to change in emotional state than neurophysiological peripheral signals. The trends and comparative analysis on the application of algorithms in newer implementations from the point of view of computer science are presented in our review, which brings about an overview of datasets, methods for identifying emotions, algorithms for feature extraction and selection, classification algorithms, and performance evaluation

4.1. Dataset Collection

Electroencephalogram signals (EEG) are an important tool in studying brain waves to assess the stress level of different initial stages and the final stages of transition of a state of mental state. EEG signals are non-invasive signals collected by placing the electrodes on the scalp part of the head in preferred functional points. The action of human neuron and a voltage variation producing electric current which the EEG measures. EEG produces different ranges frequencies based on mental state or condition of the brain.

```
[ ]  print(ds.label.value_counts())

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

Fig.3 : Raw EEG dataset used for emotion classification

A dataset could be made by recording electroencephalography (EEG) signals of a group of participants who are exposed to both positive, and negative emotions such as happiness, sadness, and normal self. The features within EEG signals are extracted via features function and the data pulled into a csv file. The csv file expands could also be separated into three status category of positive, negative, and neutral emotions. A total of 2132 EEG signals 716 – Neutral,708 – Negative,708 – Positive signals.
EEG signals recorded while participants viewed a series of emotional audiovisual stimuli, such as movies and music videos.

Collect a dataset of facial images with labeled emotions (such as happy, sad, angry, surprised, etc.). You can use publicly available datasets such as the FER2013 dataset, which contains over 35,000 labeled facial images.

	# 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
0	4.620	30.3	-356.0	15.60	26.3	1.070	0.411	-15.700
1	28.800	33.1	32.0	25.80	22.8	6.550	1.680	2.880
2	8.900	29.4	-416.0	16.70	23.7	79.900	3.360	90.200
3	14.900	31.6	-143.0	19.80	24.3	-0.584	-0.284	8.820
4	28.300	31.3	45.2	27.30	24.5	34.800	-5.790	3.060
...	...	...	...	...	...	...	...	...
2127	32.400	32.2	32.2	30.80	23.4	1.640	-2.030	0.647
2128	16.300	31.3	-284.0	14.30	23.9	4.200	1.090	4.460
2129	-0.547	28.3	-259.0	15.80	26.7	9.080	6.900	12.700
2130	16.800	19.9	-288.0	8.34	26.0	2.460	1.580	-16.000
2131	27.000	32.0	31.8	25.00	28.9	4.990	1.950	6.210

2132 rows × 2549 columns

Fig. 4: Distribution of EEG samples across three emotion categories

```
df = pd.read_csv('/content/drive/MyDrive/facial/fer2013/fer2013/fer2013.csv')
print(df.shape)
df.head()
```

(35887, 3)

	emotion	pixels	Usage
0	0	70 80 82 72 58 58 60 63 54 58 60 48 89 115 121...	Training
1	0	151 150 147 155 148 133 111 140 170 174 182 15...	Training
2	2	231 212 156 164 174 138 161 173 182 200 106 38...	Training
3	4	24 32 36 30 32 23 19 20 30 41 21 22 32 34 21 1...	Training
4	6	4 0 0 0 0 0 0 0 0 0 0 0 0 3 15 23 28 48 50 58 84...	Training

Fig. 5: Sample images from the facial emotion dataset

```
emotion_label_to_text = {0:'anger', 1:'disgust', 2:'fear', 3:'happiness', 4: 'sadness', 5: 'surprise', 6: 'neutral'}

df.emotion.value_counts()

3    8989
6    6198
4    6077
2    5121
0    4953
5    4002
1     547
Name: emotion, dtype: int64
```

Fig. 6: Classification of facial image dataset into emotion categories

4.2.EEG-Based BCI Systems for Emotion Recognition

Train the classifier: Use machine learning algorithms, such as Decision Tree Classifier, Random Forest Classifier, and Multinomial Logistic Regression to train a classifier that can predict the emotional state of the participant based on the extracted features.

Data pre-processing: The raw EEG and facial image data would likely need to be preprocessed to clean and format it appropriately for use in a machine learning model.

Data pre-processing of EEG signals consist of

- **Filtering**: EEG signals can be distorted by many sources of noise, including electrical interference from power cords and other devices, muscle activity, and intentional eye movement. Filtering techniques using high-pass, low-pass, and bandpass to eliminate noise and artifacts may be used.
- **Epoching:** EEG signals are typically segmented into epochs or segments of equal duration to facilitate analysis. Epoching can help identify occurrences or patterns in the data such as evoked potentials or sleep spindles.
- **Artifact removal:** EEG signals are affected by different types of artifacts, such as eye blinks and muscle movement. These artifacts can be removed through methods like Independent Component Analysis (ICA) that separates EEG signals into independent components and also allowing for analysis and filtering.
- **Baseline correction:** EEG signals are often compared to a baseline or reference signal to identify changes or deviations from normal activity. Baseline correction involves subtracting a baseline signal from the raw EEG data to remove any baseline drift or slow fluctuations.
- **Resampling:** EEG signals are often recorded at a high sampling rate to capture fine-grained details of the signal. However, high sampling rates can also lead to obtain a huge data files which may slow the processing time. Resampling techniques can be used to reduce the sampling rate while preserving the important features of the signal.

4.3. Human Emotion Detection using Facial Images

Human emotion detection using facial images using CNN (Convolutional Neural Network) classifier is a popular application of computer vision and deep learning. CNNs are commonly used for image classification tasks, such as recognizing faces, objects, and patterns in images.

- Preprocess the images by scaling them all to the same size and converting them to grayscale. You can also normalize the pixel values to help the model run better.
- Divide the dataset into a training, validation and testing dataset. The training dataset will be used to train the model, the validation dataset will be used to tune the hyperparameters, and measure model performance for which the test dataset will be used.
- Construct a CNN model using any of the widely-used deep learning libraries Keras, TensorFlow, or PyTorch. It is acceptable for the model to include multiple sequential layers made up of convolutional layers, pooling layers, and dense layers.
- Train the model by using the training set and validate its performance through the validation set. You should try and different hyper parameters such as batch size, learning rate, optimizer to enhance the performance and the number of epochs.
- Test the performance of the model using the testing set. You can evaluate the model's accuracy, recall, precision, and F1-score to determine its effectiveness.
- Deploy the model to detect emotions in real-time using a webcam or static images.

Overall, building a CNN classifier for human emotion detection using facial images is a challenging but rewarding task that can have various applications, such as mental health monitoring, marketing research, and human-computer interaction.

5 Experimental Results

The accuracies of the algorithms are shown in the below figures:

```
[ ] rf3=MulticlassClassificationEvaluator(labelCol="label", predictionCol="prediction", metricName="accuracy")

[ ] rf4= rf3.evaluate(rf2)

[ ] print("Accuracy = ", rf4)

    Accuracy =  0.9099264705882353
```

Fig. 7: Accuracy of Random Forest Classifier

```
evaluator = MulticlassClassificationEvaluator(
    labelCol="indexedLabel", predictionCol="prediction", metricName="accuracy")
accuracy = evaluator.evaluate(predictions)
print("Test Error = %g " % (1.0 - accuracy))

treeModel = model1.stages[2]
print(treeModel)
print("Accuracy = ", accuracy)

Test Error = 0.139706
DecisionTreeClassificationModel: uid=DecisionTreeClassifier_af8bab46df19, depth=5, numNodes=61, numClasses=3, numFeatures=412
Accuracy =  0.8602941176470589
```

Fig. 8: Accuracy of Decision Tree classifier

```
[ ] accuracy = trainingSummary.accuracy
    print("Accuracy = ", accuracy)

    Accuracy =  0.5947467166979362
```

Fig. 9: Accuracy of Multinomial Logistics Regression

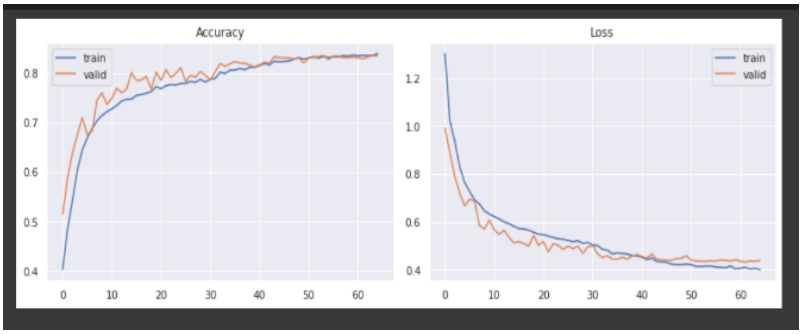

Fig.10: Accuracy and loss of Facial emotion

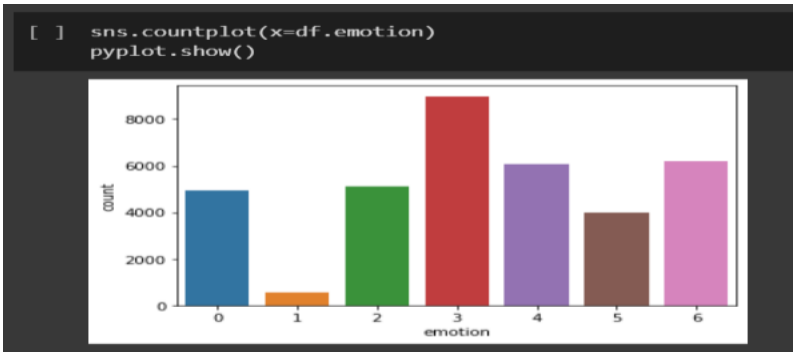

Fig. 11: Emotion classification on facial images

Therefore, the emotions are recognised using the human brain waves and facial images using the accuracies of the dataset plotted from different algorithms like Decision tree classifier, Random Forest classifier, and Multinomial logistic regression. The accuracies plotted from brain waves and facial images are compared to extract the accurate emotion.

6 Conclusion

Recognizing emotional states accurately is essential for designing systems that interact meaningfully with humans. The dual-modality method combining brainwave signals and facial imagery offers a more complete perspective of emotional conditions. This integrated approach is valuable for applications in mental health support, affective computing, and user-centric interface development. The findings underscore the importance of multi-source data in enhancing emotional intelligence in computational systems.

In normal, the emotional state of a human is the basic entity that always defines their interaction with the outside world. Therefore, emotion plays a vital role in the development of systems that require human-machine interaction.

The results of analyzing the EEG signals helps to improvise the emotion interaction with each participant. According to this evaluation, more significant rythms of signals will be inserted as a step of identifying the feature that is more active during the analysis process. The present work has several limitations that need to be acknowledged. The datasets used in this study were relatively narrow in terms of age, cultural background, and real-world variability, which may restrict how well the model performs when applied to broader or more diverse populations. Emotional responses and EEG patterns differ widely across individuals, and since the system does not include user-specific calibration, its accuracy may vary from one person to another. Implementing the framework in real time also brings challenges, as EEG signals require extensive preprocessing—such as filtering and artifact removal—and synchronizing these signals with facial images can increase processing load and delay. In addition, lower-cost EEG devices may introduce noise or inconsistent readings, which can affect reliability. The study also focused on only three emotional states, leaving out more nuanced emotions that could provide deeper understanding. These factors highlight the need for richer datasets, improved personalization techniques, stronger hardware support, and more efficient processing methods in future developments.

7 Future Enchancement

Technological improvements in emotion recognition systems can encompass greater classification accuracy with more advanced signal processing and integration of EEG and facial information with other biometric sources such as heart rate. Analytical real-time capability can also be realized for immediate use in interactive contexts. Additionally, customized emotion recognition models based on unique response patterns can enhance system dependability. Data privacy and application integrity ethical concerns will be of top priority in further developments of such technologies.

There are a variety of methods that can be used in the future for emotion detection using brain wave activity and facial recognition. These include:

Increased accuracy: One of the biggest challenges for this technology is the high accuracy levels. Advances in data processing techniques and machine learning algorithms in the future may lead to the development of even more accurate models of emotional states.The integration of brain activity and facial recognition information with oth er biometric information, such as heart rate or skin conductance, could potentially provide a more holistic view of a person's emotional state.

Real-time analysis: The majority of emotion detection systems at present require post-processing of data in order to evaluate the emotional state of an individual. Real-time analysis ability could potentially open the technology to more varied practical applications, including in mental health. treatment or in virtual reality environments.

Individualized models: People experience and express emotions in unique ways, so creating individualized models for each person could lead to more accurate emotion detection. This could be achieved by using data from a person's previous emotional responses to create a personalized emotional profile.

Ethical considerations: As with any emerging technology, it is important to consider ethical implications. Future research should consider potential biases in the data and ensure that privacy concerns are addressed. Additionally, ensuring that the technology is used for positive purposes, such as mental health treatment, rather than for surveillance or unethical marketing practices, should be a priority.

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