Automatic Recognition of Human Emotions from Electroencephalography Signals System

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ABSTRACT

Recognizing someone's emotional state could be important in our daily life affairs. Some people's emotional status can affect their performance in work either positively or negatively and they might react to the situation according to their status. Recognizing a person's emotional state can be carried by body language and facial expressions. However, people can pretend to express an opposite emotional state and hide the actual one. Using an Artificial Intelligence (AI) system of electroencephalography (EEG) human brain signals can recognize the actual person's emotional status and feelings. The proposed model stages would use a free dataset of DEAP Learning available on the internet for human EEG signals, filter the data in the pre-processing stage and specify the training and testing data, use the LSTM algorithm in the feature extraction stage to create the final model, verify the system using the testing to identify the accuracy system level. The data obtained by the analysis of EEG signals can be used in many fields like education, science, hospitals, security, and research. The design of Automatic Recognition of Human Emotions from an Electroencephalography Signals system can be considered sustainable and required for future (AI) systems development which is a growth sector around the world.

Introduction

A person's emotional state can be inferred from their facial expression, voice tone, and body language, all of which can be measured as indicators of human emotion. However, since people frequently try to conceal their emotions, it can be challenging to tell when someone is truly feeling something. They do this to avoid being in a vulnerable position and to create the desired emotional state for others in order to control their outward look.

Automatic Human Emotion Recognition from Electroencephalography Signals focuses on uncontrolled emotional states that are produced internally but are invisible to an outside observer in order to overcome what people are trying to conceal. The suggested system will receive electroencephalography (EEG) signals from the electrode sensors, process them using artificial intelligence and machine learning, and then offer the identified human emotional status.

The deep learning open-source technique of EEG signals was used to train and test the system, which was built on a raspberry pi. The suggested system will be evaluated in terms of efficiency and accuracy against the current system and will be able to recognize numerous emotional states. The suggested system will be useful in a variety of contexts, including medical patient assessments, educational development, astronaut research, unique case studies, scientific application, and any area where it is necessary to determine a person's emotional state.

The lack of input data due to people's gender, age, and other factors that could affect the system training and testing for the filtered open-source deep learning algorithms found in prior similar research is considered a limitation because the accuracy and efficiency of AI systems depend on the information.

When it comes to physiological states of human integration, emotions are the representation of various feelings, behaviors, and thoughts. They can also be psychological reactions based on interactions with loved ones, coworkers, strangers, or anything else that can alter a person's emotional state as a result of their environment and condition state. As a result, emotion plays a significant part in our daily lives and can influence our behavior and responses when interacting with others or the environment (Liu, Zhang, Li, and Kong, 2021).

The interpretation of these emotions through the face and voice can provide an estimate of the person's emotional state, but electroencephalography (EEG) signals will provide improved accuracy for the real emotions with the use of artificial intelligence and machine learning techniques. Using machine learning algorithms and deep learning techniques, research over the past few years has shown the need to identify emotional states in the fields of education, medicine, and other disciplines that focus on human psychological and physiological status (Dadebayev, Goh, and Tan, 2021).

By faking to grin, a person can convey a false sense of well-being while remaining silent about his or her actual emotional state. This will give an advantage for reading and measuring the signals to classify them and train the AI device to classify this feeling status and category them in the fields of the physiological and psychological which will help to do a proper action based on the result by the organizations. Using a camera to detect the facial emotion state will not be as accurate as taking EEG signals which will be difficult to be controlled by a person.

AI emotional recognition system using EEG signals can be used for medical research and studies that help doctors by utilizing it on patients who need medical examinations for psychological problems so they can help them receive therapies like depression. This project can also be applied to scientific research on human emotion recognition and how people respond to environmental catastrophes and accidents. It can assist persons with disabilities in identifying their emotional states and children's responses.

Literature Review

Ismail et al. (2018) investigated in their article " Human Emotion Detection Via Brain Waves Study by Using Electroencephalogram (EEG)"the use of Electroencephalogram (EEG) to identify human emotion through brain waves by creating computer software that can rapidly and accurately identify a person's emotional state. The study included raw data extraction, image capture, pre-processing, data categorization, feature extraction, and emotional face classifications. It also used visibility and EEG signals. The idea behind the study is to measure the neural activities by using human Electroencephalogram (EEG) signals. To classify emotions, the various signal waves were employed to determine each signal pattern's emotional state. The various wave forms and frequency ranges are utilized to categorize these various classes. The classification of brain wave types into five categories included an emotional description of each type in relation to the categories. Theta (3-8Hz) for Improved memory, meditation, and deep relaxation, alpha (8-12Hz) for visualization, relaxation, and creativity, beta (12-27Hz) for Concentration, and Beware, and finally, gamma (above 27Hz) is for language processing, ideation, memory, and regional learning. Delta has a frequency range of (0.5-3Hz) for the cure and very good sleep. The emotional state was categorized as being happy, sad, scared, high and low, etc. Data were simultaneously extracted from the respondent utilizing the study's approach, which involved using visual ne EEG signals. The CONTEC KT88 - 3200 EEG equipment, a camera, an electrical reconstruction of EEG signals, and an electrode connection to the participants were all used in the experiment. The above-mentioned frequency ranges were only obtained in the pre-processing stage by removing the undesired noise signals with a high pass filter and a low pass filter. The responder was asked to watch video segments of roughly two minutes in length depicting the feelings of anger, happiness, surprise, and sadness. This video featured the feature extraction step utilized to separate each emotional status for four different categories of emotional status.

The study employed a very effective methodology to create computer software that will benefit the targeted institutions, such as hospitals or police agencies. To improve the study's evaluation, the study did not include the correctness of the data findings or a comparison of the visuals with the respondent's EEG signals. Unknown participant numbers make it impossible to assess the reliability of a dataset used to create the computer software.

In the article" Development of a Real-Time Emotion Recognition System Using Facial Expressions and EEG based on machine learning and deep neural network methods"classified the emotional expressions for physically disabled people of deaf, bedridden, dumb, and autistic children based on Electroencephalogram (EEG signals) and facial landmarks by using the long short-term memory and convolutional neural network method, Hassouneh et al. (2020) discussed developing real-time emotion recognition system using EEG signals and facial expression on deep neural system and machine learning methods. The categories for emotions are surprise, disgust, happiness, fear, and rage.

The study covered how technology is used in daily life. It is accessible through a variety of systems that employ natural language processing to establish communication with humans, such as Alexa, Siri, Cortana, and others. By employing deep learning techniques to train a system to comprehend facial expressions or EEG data and provide the human's emotional state, artificial intelligence (AI), a fairly contemporary technology, can develop to incorporate emotional identification. In order to teach the system to recognize facial emotional expressions, fifteen males and fifteen females participated, while twenty-five males and thirty females participated in the system's testing and validation. The participants were about 22.9 years old on average. A greyscale image was created using a high-definition camera and sent for processing after being detected by the subject's eyes and 10 virtual markers for the action units. Using a convolutional neural network (CNN), the classifications approach generates an output labeled as Happiness, Surprise, Fear, Sadness, Anger, or Disgust. The undesirable signals, such as the effect of eye blinking or other such actions, are first eliminated from the EEG signals. Long short-term memory (LSTM) network modeling, a special kind of artificial recurrent neural network (RNN), is used to train and improve the EEG signals. This system uses an infinite impulse response (IIR) filter with frequency cutoff (1-49) Hertz to reduce noise.

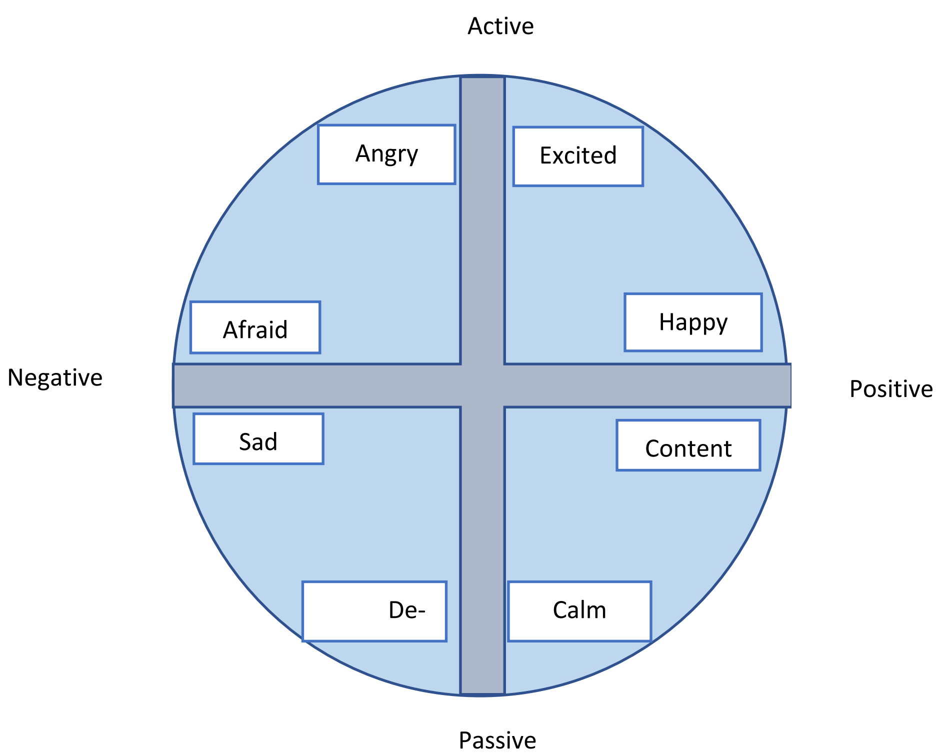

Figure 1. The Valence-arousal dimensional model.

The categorization, processing, and prediction processes all used the deep learning methodology. Nineteen participants watched a six-minute video with six distinct portions while the EEG signals were being recorded.

The study's findings demonstrated an accuracy of up to 99.81% for facial landmark emotional recognition, and an accuracy of 87.25% for EEG signal validations in the higher emotional rate of detection. If more participants were included in this study, these high percentages could be lowered. The accuracy rate for facial recognition is really high, but since humans may fake it, I believe that EEG signals are more dependable than the facial landmark technique.

Methods

Proposed System

Training Data: To train and test the system, utilize the publicly available, open-source deep learning dataset of EEG waves.

EEG signal pre-processing: Since the dataset at this stage contains just EEG signals, it must be filtered to only include 0–50 Hz signals and exclude undesirable noise signals for system training.

Feature extraction stage: At this point, the software algorithm will be applied to the EEG signal samples to extract the various classifications according to the signals channels representation of the emotions and send them to various signals categories for emotion status. Long Short-Term Memory is the machine learning algorithm that will be utilized to generate the training set model. The received signals will then be labeled for training purposes according to the categories of emotions, such as sadness, happiness, rage, etc.

Training Model of the Deep Learning algorithm: In order to build the model that will be used for the Automatic Recognition of Human Emotions from Electroencephalography Signals system on real-time EEG signals of the human to recognize his emotional status, training this model depends on the filtered dataset, which may take a very long time.

EEG data acquisition: will use electrode sensors to capture the EEG signal and deliver it to the following stage or to the dataset for training and testing.

EEG signal pre-processing: An IIR filter will be utilized to reduce unnecessary noise from the EEG signals and allow only the 0.5–50 Hz frequency range to be recorded by the electrode during system operation.

Feature extraction and selection: After the system has been trained and tested using the aforementioned algorithms in the training stage, the real-time EEG signals will be used for emotion recognition. The raw EEG signals will be used to train and test the system to categorize the open-source deep learning dataset and for accuracy improvement. Additionally, the system is used at this stage to classify the emotional state of a person and send the output to the following stage for training, testing, and real-time EEG signals.

Classified Emotion Label (happy, furious, sad, exhausted, etc.): This will provide the results of the real-time EEG of the human signals that are captured by the electrode sensors and will be used for testing to provide the prediction, output verification, and system assessment. The training phase will outline the categorization for each EEG wave the system should be trained on.

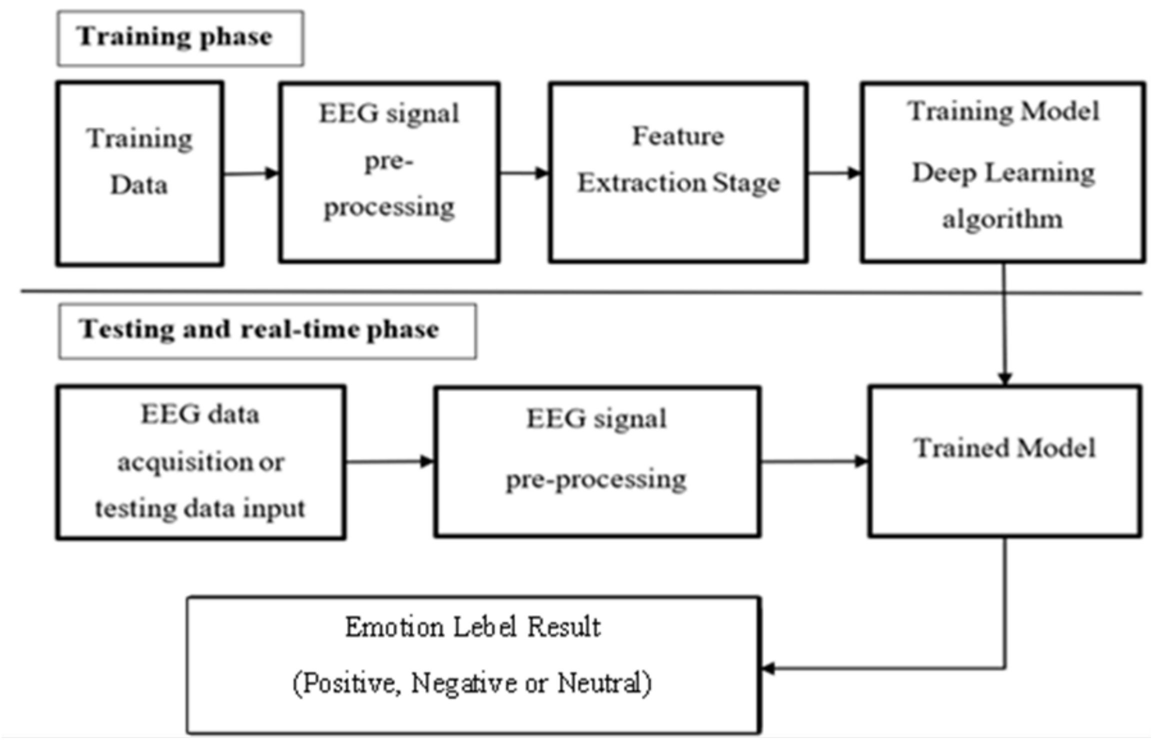

Figure 2. Automatic Recognition of Human Emotions from Electroencephalography Signals System Block diagram

System Design

To be able to accomplish the goals and objectives of the Automatic Recognition of Human Emotions from Electroencephalography Signals system, the system needs a software design that can be implemented in hardware. The software can be created using software and tools by building a program in the Python language that creates the model using a free database on the internet and uses it for real-time EEG signals. The Raspberry pi will be used as the hardware device for the implementations.

Long Short -Term Memory (LSTM)

The Automatic Recognition of Human Emotions from Electroencephalography Signals System proposed system of artificial intelligence (AI) would employ the Long Short-Term Memory (LSTM) methodology to create the model by using the training data from free sources available on the internet. The three gates that make up the LSTM's operation—the input gate, forget gate, and output gate—achieve the requirements of dependency and information processing for retaining and discarding. The hidden state that can store information and the prediction making availability, which is divided into hidden state and cell state, are the fundamental differences between the recurrent neural network RNN and the LSTM.

The fundamental structure of an LSTM comprises of t and t-1 states that are subscribed to hidden state, prior hidden state, cell state, and previous cell state.

By updating the stored information present in the previous cell state, the input signal modulation is carried out using the input gate, output gate, and forget gate, and the result in cell state will perform the operation to modify the system.

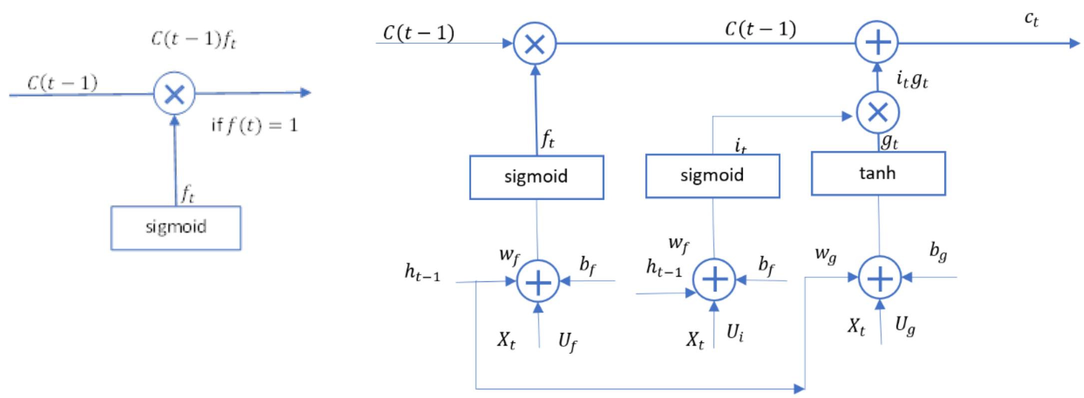

Figure 3. Long Short-Term Memory block diagram

The information kept in cell state is decided by the input gate. In order to be in cell state c(t-1), it will use what was chosen to be replaced in the forget gate. This function is performed using the formula $i_t = (x_i\, u_i + h_{(t-1)}\, w_i + b_i))$. With weight matrices of multiplications of w(i), u(i), and b(i), these input data are the results of the previous hidden state function. The sigmoid modulation for units with a range of 0 to 1 uses the sigma function. The one is for storing the data, and the zero is for not storing it.

The output gate's formula is written as $o_t = (x_t\, u_o + h_{(t-1)}\, w_o + b_o)$. The weight matrices b(0), w(0), and u(0) are multiplied in the output gate formula to perform the functions of the hidden state and the input state. Each unit is modulated using the sigmoid function. The gate input varies from 0 to 1, with 0 allowing no information to enter and 1 allowing information to pass to the output.

Cohen Kappa Score Python in Machine Learning

Efficiency testing is necessary for the Automatic Recognition of Human Emotions from Electroencephalography Signals System in order to assess the proposed system's accuracy in achieving the goals and to contrast it with the current system. For the distinct emotional recognition classification of the built model by the Python DEAP algorithm, the Kappa score is utilized to assess the machine learning performance. In order to accomplish this, the true positives and true negatives (TP&TN) agreement, disagreement, and false positive and false negative (FP&FN) rates are calculated. It is capable of processing real-time EEG signals as well as rater computations during testing and training phases for the model.

The usage of the Kappa score confusion matrix for the model classification of two classes labels is demonstrated in the example below:

• True Positives (TP): These are the agreed-upon positively predicted values that are used by both real-world and model classifier raters.

False Positives (FP) are values that are wrongly predicted as positive but are actually negative values that the model classifier raters and observer can recognize as negatives, leading to a discrepancy in the outcome.

• True negatives (TN) are the ideal agreements for the accurately predicted values used by both the model classifier raters and the observer.

• False Negatives (FN) are values that were predicted as negatives when they were actually positives by the model classifier raters and the observer, resulting in a discrepancy in the outcome.

The formula used for the Kappa score as follows:

The actual represented by rater (1) and the prediction is represented by rater (2).

The Total Observation
$TP + FP + FN + TN$ or $N = TP + FP + FN + TN$
The calculate raters for the perfect agreements is The observed agreements,

$$P_o = \frac{TP + TN}{N}$$

$$P_e = \left(\frac{P_e\ (rate1\ say\ (Yes)}{N}\right) \times \left(\frac{P_e\ (rate2\ say(Yes)}{N}\right) + \left(\frac{P_e\ (rate1\ say\ (No)}{N}\right) \times \left(\frac{P_e\ (rate2\ say(No)}{N}\right)$$

The Kappa score is calculated by the formula

$$K = \left(\frac{P_o - P_e}{1 - P_e}\right)$$

Results

Using the LSTM a model was built and the following start parameters were used:
Model: "model"

Layer	Output Shape	Param #
Input Layer	(None, 2548, 1)	0
LSTM	(None, 2548, 256)	264192
Flatten	(None, 652288)	0
Dense	(None, 3)	1956867

Total params: 2,221,059, Trainable params: 2,221,059, Non-trainable params: 0
The system training and verifying results were as following:

- The Test accuracy reached 97.188%

	precision	recall	f1-score	support
0	0.98	0.96	0.97	190
1	1.00	0.98	0.99	231
2	0.94	0.98	0.96	219
accuracy			0.97	640
macro avg	0.97	0.97	0.97	640
weighted avg	0.97	0.97	0.97	640

Figure 4. Confusion matrix result

Conclusion

The suggested AI system uses real-time EEG inputs for machine learning and artificial intelligence. The project can be applied in a variety of industries, including healthcare, education, science, and any other industry that needs to recognize human emotions. It will be created using the DEAP algorithm, and the degree of accuracy will be determined by comparing it to the effectiveness and characteristics of the current system for identifying human emotional states.

Training Database, Pre-processing, Feature Extraction, and Trained Model are the stages of system design. The Long Short-Term Memory (LSTM) algorithm approach is utilized to provide the classifications of the human emotional state. The datasets of EEG signals will be used to develop the model based on a free source of data available on the internet used for training and testing the system. The Trained Model uses electrodes of EEG signals to record human EEG signals in the range of 0-50 Hz for real-time use and will be implemented in a Raspberry Pi microcontroller.

There are many datasets types can be used but for an EEG signals is very difficult to find a good dataset that half a large numbers of participants which reduces the reliability for this type of an AI system currently however this is only a start for the near future and due to development in the technology this can be changed and more studies can be done to produce a reliable dataset that have a large number of participants which enhance the performance of the EEG signal processing and analyzing such type of data.

System design posed the biggest obstacles to finishing the project planning. The hardest part of the process is choosing the algorithm to use for the feature extraction stage because the results of various studies have not been helpful in narrowing down the best options, including Convolutional Neural Networks (CNN), Naive Bayes, Decision Trees (DT), k-nearest neighbor (k-NN), Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), and Gated Recurrent Units (GRU) classifiers. Due to my design's requirements, I currently have chosen LSTM, but I may change my mind once I see the results of the implementation stage.

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