Emotion recognition using Genetic algorithm and XGBoost

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Abstract—Emotions and their communication are what makes human beings unique from other beings. With growing technologies and necessities, there arises the need for efficient emotion recognition. It has many applications ranging from the biological field, for helping neurologically disabled people to technological science, for analyzing the amount of impact the technologies have on the emotions of people. All these require an efficient, reliable, and effective emotion recognition system that recognizes the various range of emotions with higher accuracy and little inconvenience. However, the implementation of such systems and their accuracy are affected by various factors like noise, the number of features used for classification of emotion, and many more. Hence, in this paper, we propose a method for implementing brain-computer interaction (BCI) system by using a Genetic algorithm for optimal features selection and then XGBoost classifier for emotion recognition on the output of the Genetic algorithm. All these methods are implemented on the data collected using an electroencephalogram (EEG). An analysis between conventional methods and the suggested method has been made for comparing their accuracy and effectiveness on the EEG data.

Keywords— EEG, BCI, Feature selection, Emotion recognition, Genetic algorithm, Machine learning, XGBoost.

I. INTRODUCTION

Emotions can be referred to as the state of mind in response to any external stimuli like a thing, person, or event. Furthermore, the variations in these emotions vary based on various internal and external factors like the relationship with the stimuli and frequency of occurrence. They are indeed a vital aspect of the essence of our mental life that, in turn, influences everything else.

So, it isn't surprising that there are many theories of emotions by philosophers. What is surprising is that many tended to neglect the concept during the 20th century, mostly because of the various range covered by the word "emotion," thus averting substantial theorizing. In recent decades, however, they have become the focus of real interest majorly associated with the development of technology in fields like philosophy, affective science, artificial intelligence, and such. Countless researches are progressing regarding the impact of technology on people's emotions and state of mind, and vice-versa. There is also a term called "emotion technology" that deals with sophisticated technology and scientific methods required for emotion recognition and analysis in the respective areas.

The need for the recognition of emotion spreads over a wide range of areas. They can be used in the medical field for people with neurological disabilities like amyotrophic lateral sclerosis (ALS), spinal cord injuries, and other diseases that affect the neural pathways to brain regions that emotions. Also, in scientific fields for analyzing the effects of emotions on technology for developing better technologies as per user needs, analyze trends of technological impact on humans and many more. Finding better solutions also helps in inventing new methods and concepts that may help in solution finding of other problems or optimizing present solutions for better results.

Emotions classification itself is complicated, and many models were proposed for proper definition and classification of emotions. Some popular models include the vector model and the circumplex model. Most of these models refer to the distribution of emotions on a 2-dimensional circular space of dimensions valence and arousal, some even extending to a 3- dimensional space like Plutchik's model. A detailed description of all the concepts is given in section II, followed by the proposed method in section III, then the analysis of the results in the section following it.

II. LITERATURE SURVEY

Emotions can be recognized using several external recognition features like facial expressions, speech, body gestures, and interior features like blood pressure and brain signals. Although these methods are popular due to their non-invasive nature, ease of use, and less complexity, they may not be able to recognize or classify emotions accurately. This is because of the control one has over these features and may mislead when not depicted honestly. For example, when people stay silent when they are feeling other emotions like anger or cry when they are happy. Hence, they are not exactly reliable in terms of accuracy. That is when internal features come into play.

Since one cannot control them, they provide better results and reliability. These include single modality methods like Electroencephalography (EEG), Functional Magnetic Resonance Imaging (fMRI), Positron Emission Tomography (PET). PET is an imaging test that helps in checking metabolic activity in the body, and fMRI is a blood flow monitoring method that measures brain activity in the active areas, thus causing an increase in the flow. However, these do not provide the necessary help, i.e., enough data for proper emotion recognition. Hence, we employ methods that employ brain-computer interaction (BCI), a communication platform between machines and human beings using brain signals. One example is of EEG that detects and renders brain signals via several electrodes placed on the scalp of the person [8]. It is a computer-based system that acquires, analyses, and translates brain signals to commands that are relayed to an output device to carry out the desired action, as shown in fig. 1 below. Thus, BCIs do not rely on the need for neuromuscular engagement [9].It is a widely used system due to reasons like the drawbacks of other traditional methods like fMRI, low portability, easy setup, lesser cost and complexity, non-invasive nature, and convenience.

The classification of EEG data into emotions can be done using several methods of classification. The data collected from EEG is a time-frequency variant collected over a long time with short ranges. That is one of the reasons why several machine learning approaches [1] and recurrent neural networks [6] like Long-short term memory (LSTM) [5] and artificial neural networks gives better results for EEG data. Since emotions are simply a group of feelings, distinguished by their quality from other tangible experiences, statistical methods like Gaussian mixture model [2] can be used to classify them [7]. With the rise in technology, artificial intelligence [10] also tends to provide better recognition.

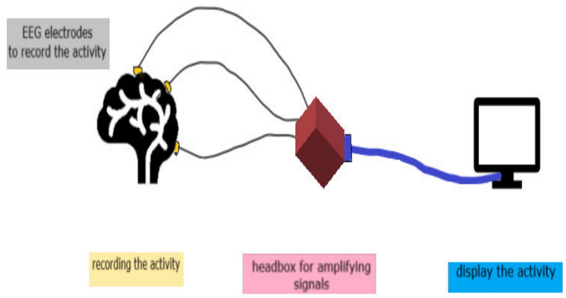

FIG. 1: EEG MODEL DEPICTION

Nevertheless, each has its disadvantage like a feed-forward network [11] and the artificial neural network that takes more time but also has better accuracy than the ones like the random forest that take less time but has lesser accuracy [3]. The accuracy of classifiers is also affected by the number of features in the dataset, which may reduce it by a more significant number in some cases. Hence, we propose a method to reduce the number of features, meanwhile increasing the accuracy, which will be explained in later sections. We used the EEG dataset like the one used in William's research [4], and the accuracy between several classifier types are also compared in later sections.The dataset has already been pre-processed of all noise and artifacts, so we are directly using it for optimal feature selection, followed by classification. The data is in temporal format, meaning time-variant, and the dimensions are of size 2132 x 2549.

Emotions can be analyzed based on multiple features like moods, affect, and feelings. Over the years, some researches later, they are divided into six basic emotions as follows - sadness, fear, disgust, anger, happiness, and surprise. Any other emotion description can be addressed as a combination of these basic emotions.
Emotions can be plotted in a 2-dimensional form using valence and arousal easily, as suggested by many models. Valence is the range of emotion from positive to negative, like happiness to sadness, while arousal is the magnitude of the emotion valence like extreme high/low happiness or sadness. If in case they are not extremely spread over both regions, i.e., closer to both axes, we consider it as neutral. Since different emotions have different arousal-valence values, output classification in the 2-dimensional plane is more straightforward. In our paper, we are classifying emotions into 3 class labels as positive, negative and neutral as shown in the fig. 2 below.

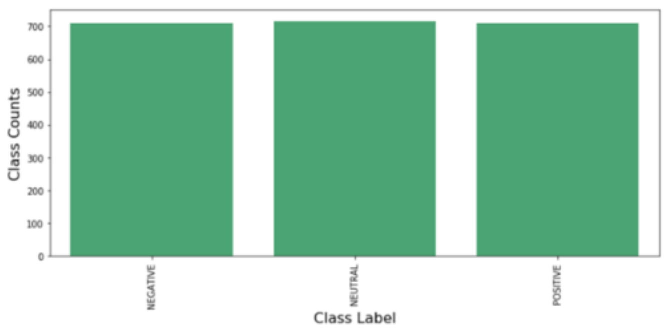

FIG. 2: EMOTION SENTIMENT CLASS DISTRIBUTION

III. PROPOSED METHOD

The data collected using EEG has many features that help in the recognition of various emotions of the person(s) from whom we obtain the data. From previous researches and surveys, we can conclude that not many classifiers achieve high accuracy in classification, at least not in a simple way. Although the ones that came close enough are artificial neural networks (ANN) like LSTM, bagging, and boosting algorithms like light GBM [12].

In this paper, we are using the XGBoost algorithm, an ensemble boosting algorithm, that took over traditional methods like regression soon after its discovery due to its characteristics of algorithm enhancement and system optimization. It is seen that it works best on tabular or similar structured data, with advantages more than any other classification or regression models.

Since the number of features in the dataset is of the high number, in our case, over two thousand features, there is a higher probability that the system may take a longer time except for few classifiers like the Random forest algorithm. So, we suggest the usage of the Genetic algorithm, inspired by Charles Darwin's theory of evolution. This not only helps in reducing the number of features but also helps in the selection of optimal features that may aid in efficient, emotion classification, thus increased accuracy.Although Random-forest algorithm can classify the data in lesser time than XGBoost, it has its disadvantages like:

- In real-time, a vast number of trees make the random forest algorithm slow for implementation
- XGBoost implements forward level-wise ensemble method instead of combining results at the end of the process like the former one.
- When parameters are finely tuned, XGBoost has better performance than the former method.

That is also one of the reasons for choosing to use optimization like the Genetic algorithm alongside XGBoost for optimal feature selection that helps in achieving efficient performance and classification.

Though the Genetic algorithm itself takes up some time for optimization and reduction, it helps reducethe time taken during the usage of XGBoostby a large scale. In the case of the implementation of a genetic algorithm, software like the GA optimization tool is available to make the process smoother, and for implementing the algorithm, we make use of python libraries and other available features.

The working of the proposed method can be depicted using a flow chart as follows:

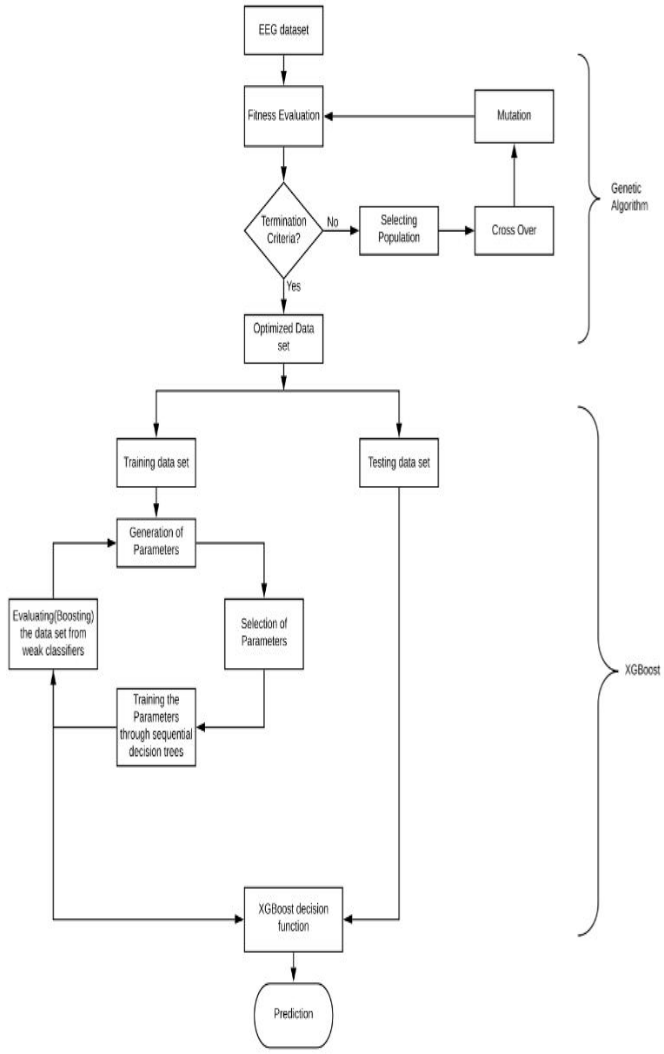

FIG. 3: FLOW CHART OF THE MODEL

The algorithm used in the proposed model is given below.

i. Select the dataset that has data collected using EEG in required format.
ii. On the dataset, perform a Genetic algorithm that has a loop of below steps [14]:
    - Apply a fitness function(f) on the selected population of fixed size with genes of length(ng) to assign fitness values(fv)
    - Use a selection parameter for selecting genes based on fv given to each one of them.
    - Perform crossover and mutation operations on the selected set of genes.
    - The new generation of population are then given to fitness function.
- The process continues in loops till the termination condition is reached, i.e., either

the generations number is reached or there is little to no change in child and parent.

iii. Now consider the new dataset with features selected using genetic algorithm and split that into two as training dataset and testing dataset.

iv. Give the training dataset to XGBoost model that works as below[13]:
   - Generate parameters and then select some of them using any technique best suits.
   - Train the parameters using sequential decision trees.
   - Evaluate the data from weak classifiers and update them using next decision tree.
   - Follow the loop of steps from step 1 till the depth of trees is reached.

v. Give the test dataset to the now trained XGBoost decision model for output.

vi. For discrete data, the output can be the mode while for continuous data, the output is the average mean of the output values.

vii. Based on the arousal-valence ranges in emotion, the values can be compared, and emotion can be predicted.

IV. RESULTS

Considering the pre-processed dataset of EEG recordings made available, the above algorithm is used, and the results thus produced are given below. The results from various classifiers are also included to be compared against proposed algorithm. It is quite certain that the suggested algorithm provides better results. Below is the table for comparison:

TABLE 1: COMPARISION OF RESULTS

Classifier	Accuracy	Total time taken
Logistic regression	0.932934052916	00:03:42
Linear SVM	0.965769382651	00:02:12
ANN	0.973748409459	00:24:15
Random forest	0.984524593041	00:00:04:55
XGBoost (without GA)	0.99390329516	00:15:29
Proposed algorithm	0.993923486241	00:07:53

V. CONCLUSION

In this paper, we present an efficient way for emotion recognition by adopting optimal feature selection using a genetic algorithm and then using XGBoost as a classifier for better results than traditional methods. Thus, we can now achieve better accuracy without having to compromise on the time taken as compared to the original methods. For the future perspective, we hope this paper helps in enhancing the emotion recognition systems for results with much better accuracy and cost.

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