Emotion Recognition System By Brainwaves

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Abstract— The paper explores single and ensemble methods to classify emotional experiences based on EEG brainwave data. A commercial MUSE EEGheadband is used with a resolution of four (TP9, AF7, AF8, TP10) electrodes. Positive and negative emotional states are invoked and neutral resting data is also recorded with no stimuli involved.

1. INTRODUCTION

Electroencephalography, or EEG, is the measurement and recording of electrical activity produced by the brain.The collection of EEG data is carried out through the use of applied electrodes, which read minute electrophysiological currents produced by the brain due to nervous oscillation. The most invasive form of EEG is subdural in which electrodes are placed directly on the brain itself. The Muse headband (shown in Fig 2 and 3)is a commercially available EEG recording device with four electrodes placed on the TP9, AF7, AF8, and TP10 positions based on the international EEG placement system. Positive and negative emotional states are invoked and neutral resting data is also recorded with no stimuli involved. The Muse headband, communicates with the computer using Bluetooth Low energy (BLE). Given figure is the EEG sensors TP9, AF7, AF8 and TP10 of the Muse headband on the international standard EEG placement system. The recorded data is trained and tested using machine learning algorithms and we analyze the test accuracy.

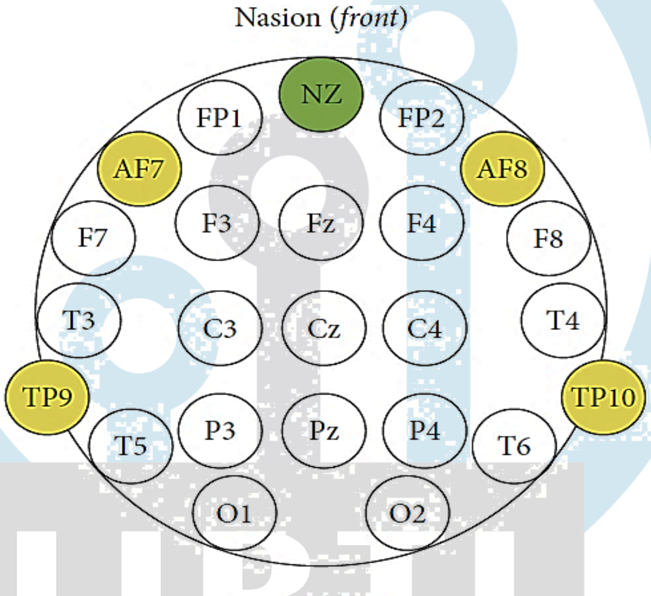

Fig 1: Emotion recognition points

Fig 2: MUSE EEG Headband

Fig 3: Model with MUSE EEG Headband

2. LITERATURE SURVEY

Autonomous non-invasive detection of emotional states is potentially useful in multiple domains such as human robot interaction and mental healthcare. Electroencephalography - Electroencephalography is the process using applied electrodes to derive electrophysiological data and signals produced by the brain. Electrodes can be subdural, under the skull, placed on and within the brain itself. Electrodes can be subdural, under the skull, placed on and within the brain itself. Machine Learning Algorithms - Decision Trees follow a linear process of conditional control statements based on attributes, through a tree-like structure where each node is a rule based decision that will further lead to other nodes. Finally, an end node is reached, and a class is given to the data object. The level of randomness or entropy on all end nodes is used to measure the classification ability of the tree [3]. A new approach to EEG data classification by exploring the idea of using evolutionary computation to both select useful discriminative EEG features and optimize the topology of Artificial Neural Networks. An evolutionary algorithm is applied to select the most informative features from an initial set of 2550 EEG statistical features [15].

3. CHALLENGES

Emotion recognition is a challenging problem in Brain-Computer Interaction (BCI). Electroencephalogram (EEG) gives unique information about brain activities that are created due to emotional stimuli. This is one of the most substantial advantages of brain signals in comparison to facial expression, tone of voice, or speech in emotion recognition tasks. However, the lack of EEG data and high dimensional EEG recordings lead to difficulties in building effective classifiers with high accuracy. In this study, data augmentation and feature extraction techniques are proposed to solve the lack of data problem and high dimensionality of data. DEAP dataset is used to evaluate the effectiveness of the proposed method. Finally, a standard support vector machine and a deep neural network with different tunes were implemented to build effective models. Experimental results show that using the additional augmented data enhances the performance of EEG-based emotion recognition models. Furthermore, the mean accuracy of classification after data augmentation is increased 6.5% for valence and 3.0% for arousal, respectively.

4. OBJECTIVES

The objective of is signal pre-processing, feature extraction and classification which will provide the emotional state. Objectives in proposed system are:

- To recognize emotions using efficient techniques.
- To get the emotions without flaws.
- To overcome difficulties in previous system.

5. PROPOSED MODEL

The proposed model (shown in Fig 4) includes:
(1) Generation of an initial dataset of biological data, EEG signals.
(2) Selection of attributes via computing with attribute selection of machine learning algorithms
(3) Optimization of a neural network via computing using machine learning algorithm.
(4) Final optimized model is evaluated.

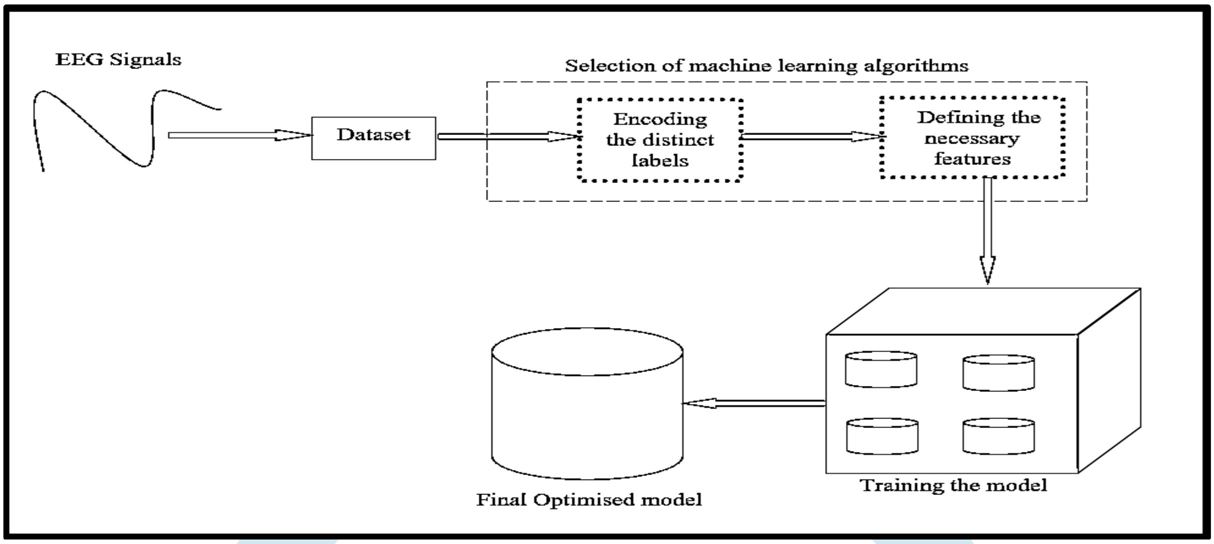

Fig 4: Proposed Model

6. DATASET

The data to be collected from two people (1 male, 1 female) for 3 minutes per state - positive, neutral, negative. We used a Muse EEG headband which recorded the TP9, AF7, AF8 and TP10 EEG placements via dry electrodes. Six minutes of resting neutral data is also recorded.

7. METHODOLOGY

Machine Learning is one of the most popular sub-fields of Artificial Intelligence. Machine learning concepts are used almost everywhere, such as Healthcare, Finance, Infrastructure, Marketing, Self-driving cars, recommendation systems, chatbots, social sites, gaming, cyber security, and many more. Machine Learning is of two types- Supervised Learning and Unsupervised Learning. Supervised Learning algorithms analyze and predict the output with the help of labeled data while Unsupervised Learning algorithms work with unlabeled data. There are 4 stages as explained in the proposed model section.As the recorded dataset is a labeled data, Supervised Learning algorithms are used. Machine learning algorithms are the in-built libraries in Python language. Using Python language, training and test the model is quite simple. The substages performed are as follows:

(1) Generation of an initial dataset of biological data, EEG signals.

- Reading EEG data with feature extracted.
- Encoding the 3 distinct labels

(2) Selection of attributes via computing with attribute selection of machine learning algorithms.

- Defining necessary features for model training.
- Defining the Model's architecture.

(3) Optimisation of a neural network via computing using machine learning algorithms.

- Training the model.

The loss function used is 'CategoricalCrossEntropy'. We also callback functions like EarlyStopping to avoid overfitting and learning rate scheduler to change the learning rate while model trains. We trained for 100 epochs starting with learningrate = 0.001 and batchsize = 64. The epoch (iteration value) considered as 5. The accuracy depends upon epoch value.

- Plotting the validation curves.

We plotted both accuracy and loss in graphical representation of tested and trained model.

(4) Final optimised model is evaluated.

- Evaluating the model

The final optimised model with test accuracy as output is obtained. The accuracy value will be great as the epoch value is increased.

8. PRELIMINARY RESULTS

The plots of validating the trained and tested model (shown in Fig 5 and Fig 6).

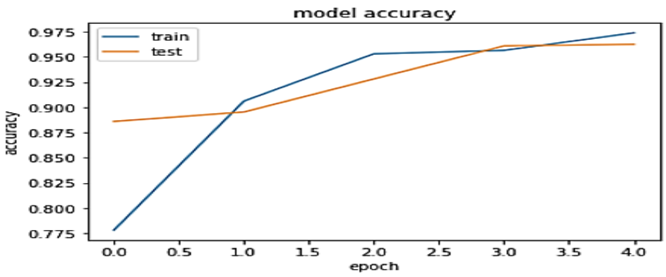

Fig 5: Accuracy plot

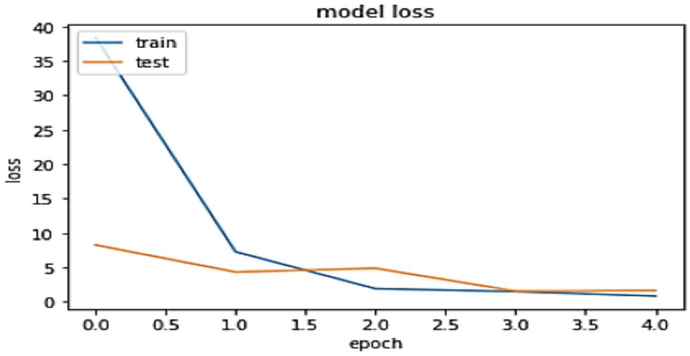

Fig 6: Loss plot

The test accuracy obtained is around 95 to 98%. Thus, the final optimized model is giving a decent and good accuracy.

9. CONCLUSION

The application of single and ensemble methods of classification to take windowed data from four points on the scalp and quantify that data into an emotional representation of what the participant was feeling at that time. The methods showed that using a low resolution, commercially available EEG headband can be effective for classifying participant's emotional state. Responding to emotional states can improve the interaction and, for mental-health systems, contribute to the overall assessment of issues and how to resolve them.

10. FUTURE SCOPE

- The existing research primarily focuses on the subjective dependent emotion recognition problem, which requires a personalized classifier for each participant. A model of emotion recognition that is subject-independent (or generic) and suitable for a collection of individuals would be extremely useful in real-world circumstances. However, to achieve emotion detection accuracy that is consistent across individuals, the subject-independent classifier model must be integrated with the transfer learning technique.
- The majority of known EEG datasets were collected using visual elicitation tools in laboratory settings. In earlier studies, the emotional condition of the subjects before the experiments were conducted was not considered. Such individual differences can cause datasets to be inconsistent.
- Many studies only considered a binary classification of each emotion dimension.
- In many emotion recognition studies, researchers examined EEG data under different emotional states and neglected the baseline (spontaneous) EEG data.
- EEG-based emotion detection of mixed emotions, such as bittersweet feelings, that integrate positive and negative influences perceived at the same time, was not found in the literature. The research to improve creative performance is linked to these mixed emotions, which is why they are interesting
- Traditionally, actual emotion classes have been labeled based on a predetermined subjective rating data threshold. Unfortunately, determining the appropriate threshold is difficult. A novel approach is to consider the valence as well as the arousal dimensions at the same time and then utilize data clustering methods to find the emotion actual classes.
- EEG-based BCI system components, such as feature extraction and selection, are continually evolving. They ought to be established on a thorough comprehension of the physiology and biology of the brain. The creation of distinctive features has the potential to dramatically improve the results of emotion detection systems. As an example, time-domain characteristics are mixed with frequency, time-frequency features, and channel location.
- Emotional models with more dimensions must be developed. Currently, the two-dimensional emotion model is widely employed. Multi-class emotion recognition necessitates the development of higher-dimensional emotion models. For example, accumulated analysis of the context information of the subject can predict the 'stance' dimension in a three-dimensional emotion model (i.e., arousal, stance, and valence).
- Advanced machine learning approaches, such as deep and transferable ML techniques, must be developed. Emotions are a reflection of cognitive processes linked to biological comprehension and psychophysiological occurrences, and their

creation is a subjective and difficult procedure. As a result, proposing a recognition method solely based on classic ML methods is problematic.

- To monitor temporal emotional fluctuations in real time, traditional time series analysis approaches must be integrated with machine learning techniques.
- The majority of engineering techniques for emotion recognition show that arousal categorization is usually more accurate than valence distinction. The rationale for this could be that arousal level changes are directly related to autonomic nervous system activities (e.g., skin conductivity and blood pressure) that are simple to measure, while the distinction of valence level necessitates a factor analysis of ANS reactions that are cross-associated. As a result, we will need to create an emotion-specific categorization framework and extract a variety of valence-relevant characteristics from EEG data in a variety of analysis domains (e.g., time-frequency, frequency, time, entropy, and multi-scale entropy).
- We need to create more datasets that employ active elicitation techniques such as video games because they better imitate “real-life” experiences and are more effective at inducing emotion.

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