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AN EEG BASED EMOTION RECOGNITION AND CLASSIFICATION USING MACHINE LEARNING TECHNIQUES

[1]C. Akalya devi, Dr. [2]D. Karthika Renuka, [3]S. Soundarya

[1]Assistant Professor (Sr. Gr), Department of Information Technology, PSG College of Technology
[2]Associate Professor, Department of Information Technology, PSG College of Technology
[3]Assistant professor,Dept. of Computer Science and Engineering, Sri Krishna College of Technology

Abstract: Emotions are complex phenomena that play significant roles in the quality of human life. Emotion plays a major role in motivation, perception, cognition, creativity, attention, learning and decision-making. A major problem in understanding emotion is the assessment of the definition of emotions. According to the WHO, every year, almost one million people die from suicide. Suicide is a leading cause of death among teenagers and adults. Existing techniques uses simple keyword search method to find emotional content in blog data and identify bloggers at risk of suicide. However, Deep sentiment analysis in suicide notes has not yet been explored much with computational approaches using advanced Machine Learning and Natural Language Processing techniques. The main contribution of the proposed work employs Electroencephalography (EEG) based psychological states for initializing the parameter weights of the neural network, which is crucial to train an accurate model while avoiding the need to inject any additional features. The Synchronized brainwave dataset contains electroencephalogram (EEG) signal values and details of the patient. The proposed methodology using Machine learning techniques to detect emotion will help individuals, industry, educational institution and Government organization to take decisions and helps people to be more comfortable in expressing their problems.

Keywords: *Electroencephalography, sentiment, psychological, Deep learning*

I. INTRODUCTION

Emotion recognition is one of the most important issues in affective computing field. Basically, human's emotion can be predicted by means of non-verbal behavior methods such as facial expression recognition, verbal behavior methods such as speech emotion recognition, or physiological signals based methods such as electroencephalogram (EEG) based emotion recognition. However, it is notable that the data recorded from either non-verbal or verbal behaviors are indirect emotional signals reflecting brain activities.

In contrast to the nonverbal or verbal behaviors, EEG signals are directly recorded from human's brain cortex and hence they could be more reliable in reflecting the inner emotional states of the brain. Consequently, using EEG data could be more accurate than behavior data when used to predict human's emotion. For this reason, the recognition of human's emotion from EEG signals has become a very active research topic in current emotional Brain-Computer Interfaces (BCI) that aims to infer the human's emotion states based on the recorded EEG signals.

A. Electroencephalogram Signals

The electroencephalogram (EEG) is a recording of the electrical activity of the brain from scalp.It is an monitoring method to record electrical activity of the brain.Typically non-invasive, with the electrodes placed along the scalp, although invasive electrodes are sometimes used such as in electrocorticography .Mostly diagnostic applications focus on either event-related potentials or on the spectral content of EEG.EEG is regularly used to analyze epilepsy, which causes variations from the norm in EEG readings.

Subordinates of the EEG system incorporate Evoked Potentials (EP), which includes calculating the EEG movement time-bolted to the introduction of a boost or something to that affect (visual, somatosensory, or sound-related). Occasion Related Potentials (ERPs) allude to found the middle value of EEG reactions that are time-bolted to more unpredictable handling of boosts; this system is utilized as a part of intellectual science, subjective brain research, and psycho physiological research.

B. Objective

To Capture user's emotional state to avoid stress-related diseases. Suicide is a leading cause of death among teenagers and adults. By identifying user emotions we can avoid suicides. Help people from mental-stress by giving them advices.

To build a training model including physiological signals(EEG signals from the Synchronized dataset) useful for detecting high levels over long periods of time or sudden increases in mental overload, emotional response, facial expression and speech of the user to detect the emotions of the users. Potentially enable solutions for monitoring of signs related to the development of stress-related diseases at work or prompt detection of acute increases in stress levels in specifically dangerous job scenarios.

II. RELATED WORKS

Most of the researchers focused only on Emotion Recognition. Simple keyword search method to find emotional content in blog data and identify bloggers at risk of suicide. Fails to predict emotion using different features such as audio-visual expressions, EEG, body gestures.

Recognition and classification of a human's continuous emotional states in real time plays an important role in machine emotional intelligence and human-machine interaction. Emotion recognition from EEG signals allows the direct assessment of the "inner" state of a user, which is considered an important factor in human-machine-interaction.

In paper [1],they deal with EEG emotion recognition problem, adopt the popularly used frequency feature to describe the EEG signal by dividing the full EEG frequency band into five parts, and frequency bands, and then extract the frequency band features from each band for GSCCA model learning and emotion recognition. Finally, conducted extensive experiments on EEG-based emotion recognition based on the SJTU Emotion EEG Dataset (SEED) and experimental results demonstrate that the proposed GSCCA method would outperform the state-of-the-art EEG-based emotion recognition approaches.

In paper [2], many methods for feature extraction have been studied and the selection of both appropriate features and electrode locations is usually based on neuro-scientific findings. Their suitability for emotion recognition, however, has been tested using a small amount of distinct feature sets and on different, usually small data sets. A major limitation here, that no systematic comparison of features exists. Therefore, review feature extraction methods for emotion recognition from EEG based on 33 studies.

An experiment conducted for comparing these features using machine learning techniques for feature selection on a self recorded data set. Results are presented with respect to performance of different feature selection methods, usage of selected feature types, and selection of electrode locations. Features selected by multivariate methods slightly outperform univariate methods. Advanced feature extraction techniques are found to have advantages over commonly used spectral power bands. Results also suggest preference to locations over parietal and centro-parietal lobes.

Classification problems are supervised machine learning problems where the task implemented to predict a discrete class for a given input. A typical example for the handwritten digit recognition where the input image of a handwritten digit, and the output in the form of discrete categories. As in all supervised learning problems the training data consists of a set of example input-output pairs.

In paper [4], all the signals were captured using portable, wearable, wireless, low-cost and off-the-shelf equipment that has the potential to allow the use of affective computing methods in everyday applications. A base for participant-wise emotion recognition using EEG and ECG -based features, as well as their fusion, was established through supervised classification experiments using Support Vector Machines (SVMs).

III. DEEP LEARNING VS TRADITIONAL MACHINE LEARNING

Deep learning is one of the main strategies by which we can go around this test of highlight extraction. This is on the grounds that the Deep learning model empowers machines of figuring out how to concentrate on the correct highlights without anyone else, requiring little direction from the software engineer. This makes Deep learning into a great degree effective device for current machine learning. In my feature work, EEG has been classified using Deep Learning.

Sometimes, an encounter issues for which it's difficult to compose a PC program. Perceiving written by hand digits, perceiving objects, understanding ideas, grasping discourse, are some such monotonous issues. This is on the grounds that it turns out to be very convoluted to aggregate a rundown of heuristics that precisely arrange diverse example sets for each of these issues. This inconvenience is looked with conventional machine learning models, and is known as a feature extraction refer fig.1.

Feature extraction includes the requirement for the software engineer to explicitly tell the PC what sort of things it ought to search for that will be instructive in settling on a choice. This places a colossal weight on the software engineer, and the calculation's viability depends intensely on how savvy the developer.

Machine Learning is a first-class ticket to the most exciting careers in data analysis today. Machine learning is the science of getting computers to act without being explicitly programmed. As data sources improves along with the computing power to process them, most straightforward ways to quickly gain insights and make predictions. Machine learning is so pervasive today that we use so many times in our daily life without knowing it. It must have skill for all aspiring data analysts and data scientists, or anyone else who wants to make all that raw data into refined trends and predictions.

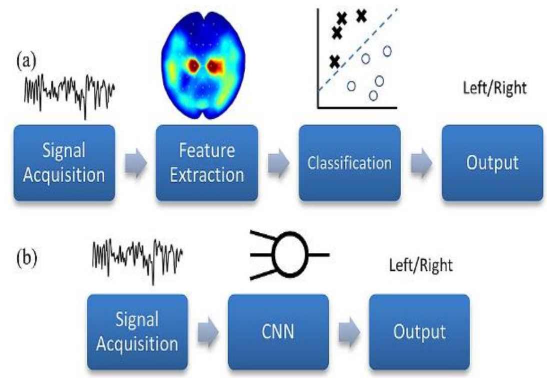

Fig.1 :Deep Learning vs Traditional Machine Learning

IV. IMPLEMENTATION ENVIRONMENT

A. Anaconda

Anaconda is a free open source distribution environment using Python and R programming languages for large-scale data processing, predictive analytics, and scientific computing, that mainly aims to simplify package management and deployment. Package versions are managed by the package management system conda.

B. Tensor Flow

TensorFlow is an open-source software library for machine learning across a range of tasks. Tensorflow is used as a system for building and training neural networks to detect and decipher patterns and correlations, analogous to human learning and reasoning. It has a flexible architecture and allows as for easy deployment of computation across a variety of platforms like CPUs, GPUs, TPUs.

TensorFlow was developed by the Google Brain team for internal Google use. It was released under the Apache 2.0 open source license on 9 November 2015.Tensorflow in windows operating system is installed in the Anaconda environment.

C. Jupyter Notebook

In Anaconda environment it is easy to install python, the jupyter notebook and spyder is mainly used to run python programmes, and other commonly used packages for scientific computing and data science. Jupyter notebook runs code in many programming languages, but python is used mainly for the requirement of installing the jupyter notebook. It can be executed on a local desktop, requiring no internet access or can be installed on a remote server and accessed through the internet.

V. DATASET DESCRIPTION

EEG devices are becoming cheaper and available now a days, but few applications leverage EEG data effectively, in part because there are few large repositories of EEG data.

The MIDS class at the UC Berkeley School of Information is sharing a dataset collected using consumer-grade brainwave-sensing headsets, along visual stimulus used to collect the data. The dataset includes readings from before the start and after the end of the stimulus.

EEG data

The receiver receives data packet every second from each Mindwave Mobile device, and stores the data in a row entry with the following data fields:

id, indra_time, browser_latency, reading_time, Neurosky values, label

id: Integer value in the range of 1 to 30 representing the subject. You can cross-reference these with subject-metadata.csv to learn more about each subject.

label: The task that the subject was doing at the time of the recording.

Neurosky values

The remaining five fields are defined by the Neurosky SDK:

raw_values: Tuple containing raw sample values acquired by the sensor, at a sampling rate of 512Hz.

attention_esense and meditation_esense:

Attention and Meditation levels, in integer values in the range of 0 to 100.

eeg_power: Represents the magnitude of 8 commonly-recognized types of EEG frequency bands -- delta (0.5 - 2.75Hz), theta (3.5 - 6.75Hz), low-alpha (7.5 - 9.25Hz), high-alpha (10 - 11.75Hz), low-beta (13 - 16.75Hz), high-beta (18 - 29.75Hz), low-gamma (31 - 39.75Hz), and mid-gamma (41 - 49.75Hz)..

signal_quality: A zero value indicates good signal quality. The signal value of above 128 corresponds to a situation , headset is not worn properly by that person.

VI. PROPOSED METHODOLOGY

In the proposed methodology, develop a method of detecting and classifying emotions of users through Machine Learning networks and validating it using real time EEG signal analysis.

- To build a Neural Network model including physiological signals (EEG signals) useful for detecting emotions of the users.

This will potentially enable solutions for monitoring people of signs related to the development of stress-related diseases at work. The work flow of the model is represented in fig.2.

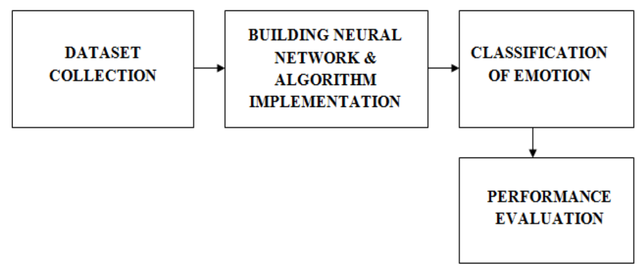

Fig.2 :PROPOSED MODEL

Steps to be followed for classification of emotions,

1. Loading the data set.
2. Defining the network structure.
3. Setting initial values for weights and bias.
4. Generate stronger feature vectors.
5. Training the network.
6. Testing the network.
7. Classification of emotions.

VII. CLASSIFICATION OF EMOTION

Deep learning methods are very good at classifying the inputs and it gives better results when compared to other algorithms. It gives accurate predictions and analysis results, and it is a benchmark for this type of large datasets. Classification is to differentiate or to categorize the inputs given, the process in which ideas are recognized, differentiated, and understood. It is a way of assigning a class label to a set of unclassified cases.

1.Supervised Classification - The set of possible classes is known in advance.

2.UnsupervisedClassification - Set of possible classes is not known. After classification we can try to assign a name to that class.

Emotions can be classified using various machine learning algorithms refer figure 9.1,

The machine learning classification algorithm used here for classifying emotions with the help of neural network are

- K-Nearest Neibours Algorithm.
- Decision Tree Algorithm.
- SVM(Support Vector Machine) Algorithm.
- Softmax Classifier Algorithm.

A. K-NEAREST NEIBOUR CLASSIFIER

The KNN algorithm is a benchmark classifier, which is often used for more complex classification. Despite its simplicity, KNN acts as a more powerful classifiers and is used in most of the applications today. KNN was leveraged in the year 2006 for the assignment of genes based on their expression profiles, but now it is used in many fields for classification and provides very good results.

In k-NN classification, the output is a class with similar instances. The input given by us will be classified by a majority vote of its neighbors, with the given k-value being assigned to the class, most common among its k nearest neighbors. If k = 1, then the object is simply assigned to the class of that single nearest neighbor. The k-NN algorithm is among the simplest of all machine learning algorithms. KNN algorithms use a data and classify new data points based on a similarity measures. It is a supervised machine learning algorithm. K-NN must probably used first when there is no knowledge about the input data. Here K-NN is used mainly for emotion recognition; the emotions are classified by EEG signal values. The values for K is given by us and the output from that is considered and classified as different types of emotions(positive and negative).

B. DECISION TREE CLASSIFIER

Decision tree learning uses a decision tree is a systematic approach to build classification models from an input data set. The decision tree classifiers organized a series of test questions and conditions in a tree structure. A test condition (i.e. yes or no) is applied to each and every nodes of a decision tree. The test process starts from the root node, and the test condition is applied to the input record and follow the appropriate branch based on the outcome of the test. However, more efficient algorithms can be used in this decision tree classifier to get more accurate and better classification results. EEG signal values are given as a input to the decision tree classifier, the decision tree is constructed in order to classify the EEG values and provides results as different types of emotions(positive and negative).

C. SUPPORT VECTOR MACHINE (SVM)

In machine learning, support vector machines are supervised learning models which is mainly used for classification and regression analysis. A decision plane is used here, it is plane that separates between a set of objects having different class members. SVM is commonly used for image recognition challenges, performing particularly well in aspect-based recognition and color-based classification. Support vector machines are not necessarily better than other machine learning methods, but they perform at the state-of-the-art level and have much current theoretical and empirical appeal. SVM is considered as a better algorithm by many of the researchers for performing classification. The input EEG signal values is given into the SVM classifier and the emotions are classified using SVM by the hyper plane drawn by identifying the emotions.

D. SOFTMAX CLASSIFIER

Two different types of classification algorithm is used mostly in machine learning, that is supervised classification and unsupervised classification. In Deep learning there are three types of classification algorithm they are supervised, unsupervised and reinforcement learning. Supervised classification will provide better results when compared to unsupervised classification. Softmax classifier gives you probabilities for each class label, it is used in the last layer of neural network classifier. A softmax classifier is a model which converts unnormalized values into normalized values and provide input to the classifier. Unlike other classifiers, Softmax classifiers which treats outputs as scores for each class. Softmax function is used for finding the cross entropy loss. Softmax classifier provides probabilities for each class, the correct class will have higher probability and incorrect class will have lower probabilities.

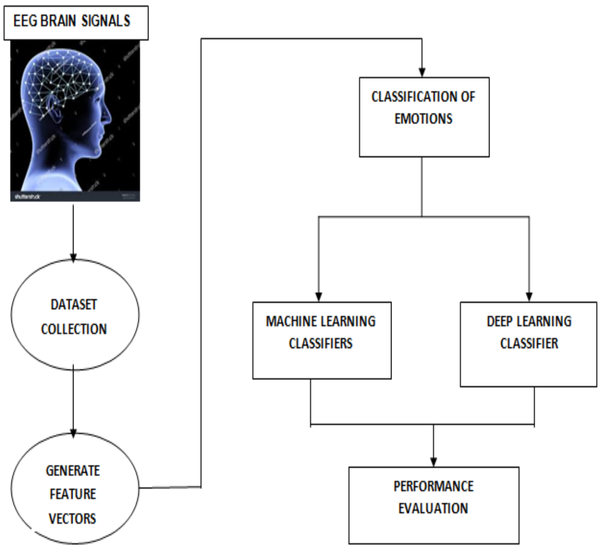

Fig.3 : Overall framework

VIII. RESULT ANALYSIS

Emotions are classified using synchronized brainwave dataset, the dataset contains three different files, they are

- Stimulus-timing.csv
- Subject-metadata.csv
- EEG data.csv

The feature vectors are generated with the help of tensorflow itself, by removing unwanted labels and values in the dataset the feature vectors were generated and splits into train and test data for classification of emotions. The emotions are classified into 2 types,

- Math (abnormal behaviour of the user).
- Relax (normal behaviour).

Emotions classified using different classification algorithm and accuracy calculated for each classification algorithm. With help of accuracy the performance calculated for each method and evaluated, refer fig.3.

As a result of softmax classifier,

```
relax    30
math     30
Name: label, dtype: int64
       id  label        0        1        2        3        4       5
13277   1  relax   85497.0  20547.0   2723.0   3270.0   2522.0  2209.0
13291   1  relax   50036.0  57439.0  17659.0   5816.0  10021.0  2917.0
13305   1  relax  155790.0  43496.0  14414.0   8105.0   8255.0  7485.0
13323   1  relax  160552.0  44796.0  13555.0  21970.0  12998.0  4266.0
13338   1  relax   18471.0  31938.0  35127.0  14536.0   8849.0  4532.0

            6       7
13277   449.0   393.0
13291  1030.0  1264.0
13305  2610.0  4343.0
13323  2635.0  1820.0
13338  2445.0   670.0
```

Performance can be evaluated using different classifier method results, cost for each iteration is calculated.

ITERATION COST

```
epoch is 0 and cost is 66.83113861083984
epoch is 500 and cost is 59.68346405029297
epoch is 1000 and cost is 49.786338806152344
epoch is 1500 and cost is 40.71527862548828
epoch is 2000 and cost is 36.82926940917969
epoch is 2500 and cost is 35.12858963012695
epoch is 3000 and cost is 34.49428176879883
epoch is 3500 and cost is 33.727516174316406
epoch is 4000 and cost is 33.03241729736328
epoch is 4500 and cost is 32.543067932128906
epoch is 5000 and cost is 32.68738555908203
epoch is 5500 and cost is 32.36553192138672
epoch is 6000 and cost is 32.42988586425781
epoch is 6500 and cost is 31.841323852539062
epoch is 7000 and cost is 31.877710342407227
epoch is 7500 and cost is 31.759809494018555
epoch is 8000 and cost is 31.618532180786133
epoch is 8500 and cost is 31.627424240112305
epoch is 9000 and cost is 31.548927307128906
epoch is 9500 and cost is 31.461074829101562
```

Accuracy for each algorithm is calculated and compared to find which one will be the best in the comparison table refer table 1.

Table 1: COMPARISON TABLE

METHODS	ACCURACY
K-NEAREST NEIGHBOR	66.16%
DECISION TREE	60.36%
SUPERVISED VECTOR MACHINE	68.29%
SOFTMAX CLASSIFIER	75.42%

IX. CONCLUSION AND FUTURE WORK

Emotions are very important in human decision handling, interaction and cognitive process. Thus the emotions classified using Machine learning classification algorithms such as Softmax classifier, K-NN classifier, Decision tree classifier, SVM(Support Vector Machine)with the help of neural networks. The accuracy of the result must be considered in order to get better performance by having more number of hidden layers in the neural network. Softmax classifier got better accuracy when compared with other machine learning classification algorithms. The accuracy got from softmax classifier 75.42% gives better results when compared to other machine learning classification algorithms. Consequently, using EEG data could be more accurate than behavior data when used to predict human's emotion. Further enhancements done with the emotions, classified using image and video dataset using deep learning algorithm like convolutional neural network.

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