Machine Learning Based Human Attention Recognition From Brain-EEG Signals

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***Abstract*—Emotion recognition has always been a very popular field of research. Recently, EEG brain waves are being used to recognize the emotional states of a person. Apart from the emotional state of a person, the attention level also plays an important role in human life. However, human attention level research still demands more investigation. This paper proposes a cost-effective single-channel time-frequency scalp-EEG signals based noble human attention level recognition system using advanced machine learning algorithms. In this study, the Bitalino EEG sensor board has been used to record EEG signals from 30 human subjects in different attention states. Initially, the attention level was classified into three categories which are focused, neutral and distracted. The data was taken while the subjects were watching interesting videos and boring lectures, doing simple and interesting math and solving interesting and hard puzzles. At first, these EEG signals are pre-processed to remove noise such as muscle movement. Statistical coefficients (i.e. mean, standard deviation, skewness, kurtosis, and entropy) and statistical wavelet transform are used to extract meaningful features from the EEG signal. We mainly used two Multi-scale Wavelet Packet Statistics (WPS) and Multi-scale Wavelet Packet Energy Statistics (WPES) to generate the feature vector. This feature vector was used to train the complex hybrid model with CNN and LSTM. This proposed method achieved almost 89% accuracy while determining the attention level of a subject.**

***Index Terms*—EEG(Electroencephalography), Brainwave, Wavelet Decomposition, Deep Learning etc.**

I. Introduction

Brain and the study related to brain has always fascinated the mankind. Be it the medical science, be it the psychology studies or be it any studies related the computing science field, the study of Brain signals never failed to offer more to the betterment of human race. Not long before the detection of brain tumor was not possible from analyzing the X-rays or Brain waves. A rigorous study with brain signals has sufficed us to detect not only Brain Tumors from Electroencephalograph but also many brain related diseases like Alzheimer's disease [5], sleep disorders [1] or Fatigues of driver's cognitive states [9].

Whatever a human body does affects the brain. Consequently, a fluctuation of electrons flow across the 100 Billions neurons that form the neural network of human brain thus producing a variance in the Brain-EEG signals. And the researchers address these changes in the EEG signals produced from brain for variety of experiments. In [2], [4], [6], [10], [11] authors demonstrated quite well on how Machine Learning approaches can be used in emotional states classification.

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Albeit numerous experiments have taken place in detecting diseases or classifying human emotions, nobody was talking about Human Attention level recognition. So what is Human Attention Level? Simply put, it refers to the different states of the human brain while you are putting your brain to any task. Like a student can be either attentive or inattentive during lectures. And the student's brain will never function in the same way for both cases, from which the experiment material of this paper stems.

In this paper we have addressed the untouched domain of Human Attention Level recognition, and the students are taken into consideration on our first attempt. This community forms the majority of the data collection domain for these studies, but attention level can also be studied on various other domain like- office employees, pilots etc. Our work has developed a novel Machine Learning and Deep Learning based Human Attention Level recognition model using Brain-EEG which can identify the attention level of a single human being at an instance.

II. The Specifics of Electroencephalography

A. *Composition of a raw EEG signal*

Electroencephalography(EEG) is an electro-physiological checking technique to record electrical movement of the cerebrum. It is regularly noninvasive, with the terminals set along the scalp, albeit obtrusive cathodes are now and again utilized, as in electro-corticography. EEG measures voltage vacillations coming about because of ionic current inside the neurons of the cerebrum.

A raw EEG signal(Fig. 4) consists of several frequency sub-bands: Gamma(>30Hz), Beta(13-30Hz), Alpha(8-12 Hz), Theta(4-8Hz), and Delta(<4Hz). But a raw EEG captured from any human interferes from a lot of Noises on account of unwanted Muscular movements or outside phenomena [14].

In [3], we get a clear picture of how a raw EEG signal is to be decomposed to the sub-bands. It's a trivial method, and in our work we used some advanced functions of *Matlab2019a* based on this model in Fig.2

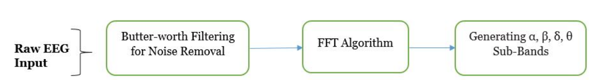

Fig. 1. Workflow to decompose raw EEG

B. Machine Learning and Deep Learning studies on EEG

The dangling of researchers with ML and DL based classification of different brain states or diseases or emotional states has been going on for quite a while now. [1], [8] stated a comparative analysis of different Machine Learning algorithms' performances in attempt to classify EEG signals. In [9] *Bhardwaj et. al.* presented us with a in depth analysis of different ML and DL based algorithm while classifying EEG. In the paper the authors compared SVM, KNN, DT, Autoencoder, Ensemble.

In another study [6] *Lin et. al.* attempted to classify human emotions from listening to music applying. Same approach was improved by *Peng et. al.* in [7] where they used manifold regularized extreme learning machine using advanced algorithms like GELM, MRELM etc. over SVM.

The basics of EEG breakdown is easily described in [3], whereas *Kher et. al.* described how to capture raw EEG signals with wireless transmission in [14]. With time we saw the uses of recent ML and DL algorithms for classifying EEG signals. With advanced algorithms like LSTM-RNN, *Jeevan et. al* recognized different human emotions with higher accuracy in [4]. In [10], *Amin et. al.* took on Pattern Recognition approaches to classify EEG signals. We also found the use of deep recurrent convolutional neural networks to classify EEG in [11] by *Bashivan et. al* and in [13] *Subasi et. al.* used mixture of expert models with the same intention.

Apart from these EEG signal classification is used in detecting Seizures, Alzheimer's disease, Driver's fatigue stages, Human sleeping stages, Brain Tumor, Strokes, Dementia etc. diseases.

III. Human Attention Recognition and Our Proposal

If your mind hasn't fluctuated attention states during your studies then there is something wrong with you. No one in this world can keep 100% attention throughout the whole lecture. Sometimes one adheres to his/her studies fully(**Attentive Mode**) or sometimes goes into excited state(**Happy or Sad**) leaving study or sometimes s/he just does nothing(**Neutral Mode**).

Although a whole lot of works has been done on classifying human emotions or diseases, almost no work is being done as of yet which targeted the human attention levels. The changes in human EEG signals during different attention levels for the students have never been taken into consideration for study. The community is a pond full of fishes to catch Brain-EEG signals.

Therefore, in this paper we devised a novel machine learning based Human Attention recognition model using raw Brain-EEG signals. Throughout the work we built our own data-set for training & testing, and built our complex hybrid model using- CNN & LSTM.

IV. Data Collection and Setup

A. Device used : Bitalino

For data collection we used the "(R)evolution Plugged Kit BT" from *Bitalino Inc.(https://bitalino.com/en/)*. This device features ability to capture EEG, ECG, EMG, EDA signals and also comes with a software which stores the real-time data in the host workstation in *text* or *edf* format.

B. Target Audience and Our Data

There were 20 participants where the EEG signal was recorded twice from each participant. Therefore, we have 40 instances of EEG. Each instance of EEG is 8 minutes(480 seconds) long. The signals that we have collected were of students from the University of Asia Pacific, Bangladesh all aged between 21 to 25 years. Through our data collection we recorded FOUR attention states which are- **Happy**, **Attentive**, **Sad/Bored**, and **Neutral**. Fig. 2 will give you the idea on a whole data collection procedure, and what we did to change the student's attention states.

Fig. 2. Data Capture process

V. Experimentation Setup

A. Data Pre-processing

The main point of data collection is manual labeling. At first, we observed how the signal looks like in a neutral state. We took three types of data which are Calculation, Happy, and Boring as attention levels. While a person solving an interesting math problem, his EEG pattern changed abruptly. However, this pattern does not persist throughout a whole session. That abruptly changed part implies the attention states out of a full raw EEG signal.

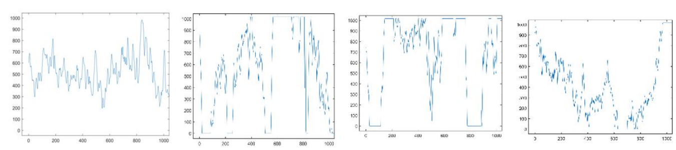

Fig. 3. Neutral, Attentive, Happy, Boring States

We recorded the starting and ending time of the attention period. The attention period and the attention level depends on the nature of the task and the surrounding environment. After several tests, we found it normally lasted for 1-2 seconds. We want to classify a person's states into 4 classes- Neutral, Attentive, Happy, and Boring states. The attention state was manually segmented from the raw EEG signal. The sampling rate of the EEG signal was 1000Hz. The segment length is 2 seconds which consists of 2000 data points. Every session (120 seconds) is segmented into 20 slots (consists of 2000 data points). These slots represent an active attention zone.

B. Feature Extraction

The features can be classified into two types- time-domain and frequency-domain features. Time-domain features are different types of statistical features like mean, variance, power, peak to peak difference, etc. The frequency-domain features are related to the decomposition of the raw signals into sub-signals.

In our experiment, the raw EEG was decomposed into sub-bands using a 1-D wavelet decomposition function in Matlab. The signal was decomposed into 8 levels where each level represents different features. The detailed coefficient of levels 1 to 4 represents noise. So, these four bands were removed from the analysis. The rest of the detail coefficients of wavelet decomposition levels 5 to 8 represent gamma, beta, alpha, and theta sub-signals. The approximation coefficient of level 8 represents delta sub-bands. These sub-bands are very useful for EEG signal analysis(Fig. 4).

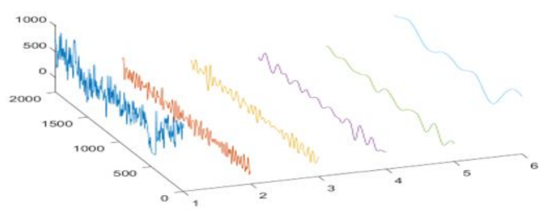

Fig. 4. 1-Raw, 2-gamma, 3-beta, 4-alpha, 5-theta, 6-delta. The length of the signal is 2000 and the z-axis represents the amplitude of the signals.

Now we applied two functions on these sub-signals. One is **Welch's Power Spectral Density Estimate(WPSDE)** and another function is **Spectrogram** using a short-time Fourier transform(STFT). The length of each sequence was 2 seconds where there were 2000 data points as the sampling rate was 1000Hz. Now, a number of statistical features were calculated considering a fixed window size of 100 milliseconds and the slide step size being 10 samples[1]. Mean, Variance, Skewness, and Kurtosis were calculated from this signal using this sliding window configuration(Fig. 5).

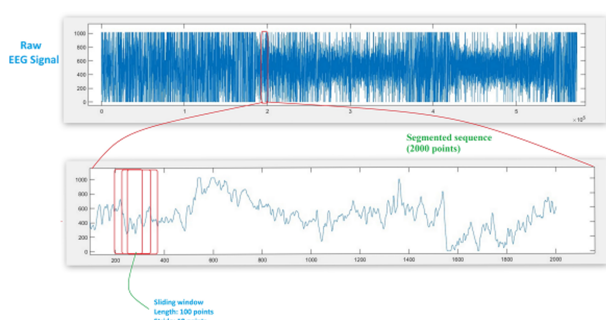

Fig. 5. Raw signal segmentation and sliding window for calculating statistical features

[1] 1 sample= 1 milisecond

Welch's power spectral density estimation(WPSDE) of all the sub-signals are taken as input features. Fig. 6. demonstrates the WPSDE calculated from our data-set. The four statistical values are also taken as input features. The feature vector consists of 1 raw signal, 5 sub-signals, 24 statistical values (6 signals x 4 statistical formula), 6 Welch's power spectral density estimation of each signal. In total there are 48 values in the feature vector.

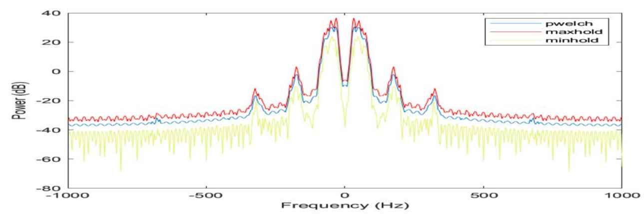

Fig. 6. Welch's Power Spectral Density Estimate

Spectrogram of a signal is the Power distribution in the time-frequency domain. The visual representation of the spectrogram is very important for signal analysis. Therefore, the spectrogram function was applied to 6 signals. Among them, the spectrogram of raw, beta, and alpha signal was selected for analysis(Fig. 6). This selection was based on empirical reasons and simulation of the deep learning model.

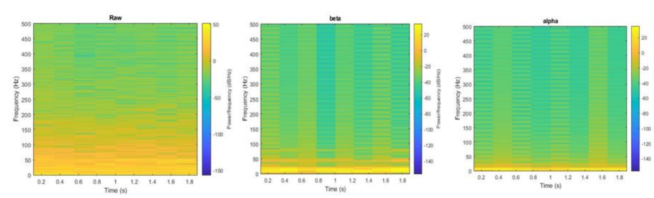

Fig. 7. Spectrogram of Raw, Beta and Alpha signal

C. The Hybrid CNN-LSTM Model

From III, we know that in our work we built a Complex Hybrid model using *CNN(Convolutional Neural Network)* and *LSTM(Long-Short Term Memory)*. The LSTM is used for sequence classification. The data-set consists of a sequences and images. Each sequence is 2000 points long and has 48 features. So, the input dimension of LSTM is (40, 2000, 48) where 40 represents the instances of EEG. In paper [15], [16] a similar approach an artificial neural network was used for signal classification.

The visual data-set consists of Spectrogram of raw EEG, beta and alpha signal. All the Spectrogram images were converted into 64x64x3 dimensions where 64x64 represents the height and width and 3 represents the RGB layers. Three CNN input layers take spectrograms of raw, beta, and alpha signal. And one LSTM input layer takes the sequential input. The output layer from each sub-models in concatenated into one layer followed by dense layers.

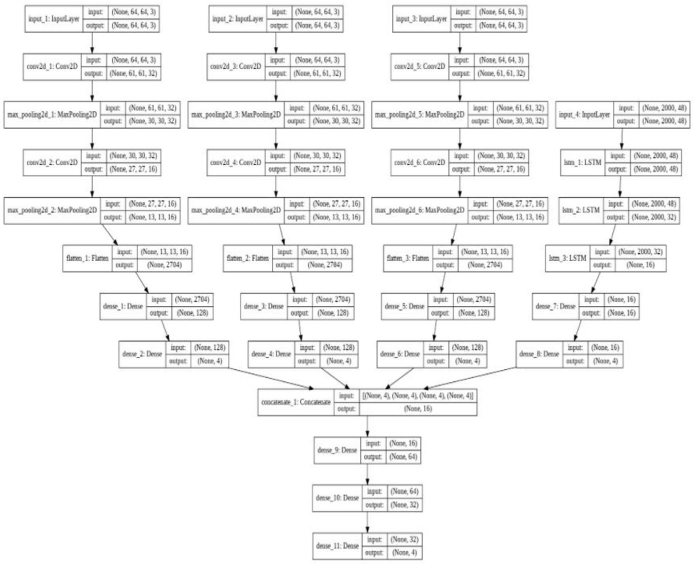

Fig. 8. Hybrid Deep Learning Model

VI. The Experiment and Result Analysis

The whole building, training and testing the model part were done on 'Python' environment using- *JetBrains PyCharm* and *Kaggle*. But before that *Matlab 2019a* helped us with V-A & V-B for processing our data to build up the inputs for our CNN-LSTM model.

The developed learning model acquired an astounding accuracy of 89% which can differentiate among Neutral, Attentive, Happy or Sad. The model, during our calculation, takes about .0125 second for it's learning period.

VII. Future Works

With relation to this developed model, we will be focusing on two main future targets. They are-

- We believe our data-set contained average numbers of data which needs to be increased. With that we aim to secure a higher accuracy with our model with increased no. of features.
- A community-based implementation of our model to build up a *Classroom Attention Level Recognition* system which can capture numerous EEG signals at once and process them for an ultimate result.

VIII. Conclusion

In the present study, a novel model using deep learning methods is devised for human attention states recognition which can contrast among four states. After the filtering and the segmentation processes, spectral density and spectrogram analyses are implemented to fetch out features from the EEG recordings. The CNN-LSTM based model is used as a classifier. which on experimenting on our self built data-set illustrated that a satisfactory and empirical execution can be reached by means of the proposed framework.

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