Improvement in the brain activity monitoring using EEG Signal Analysis and Convolution al neural network

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Abstract

Electroencephalography is a method to analyze electrical activitiespresent in the different parts of the human brain and using visual trace it records these activities.EEG provides cost effective, portable, high frequency and accurate measurement as compare to other brain wave activity monitoring tool. The electrodes present in EEG test detects tiny electrical charges that result from the activity of brain cells. The interpretation of this large EEG signal provides increased accuracy for analyzing brain functionality. Traditional method of analysis of EEG signal relies more on the trained experts. In the proposed research using machine learning techniques and spatial temporal data the classification task of EEG signal analysis is performed with more accuracy and in time efficient manner. In this research sliding window protocol with specified window size is used for generation of training data for deep learning network and to standardize the training data for enhancement of model's performance. For the accuracy comparison variantsofrecurrentneuralnetwork and Convolutionalneuralnetwork is analyzed using the collected dataset. Result analysis shows that the convolutional neural network produces high accuracy and training efficiency when compare with different machine

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learning model.

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I. INTRODUCTION

For enabling effective human-machine interaction, a brain computer interface (BCI) can directly link brain activities and external devices. In addition to helping people understand the functions of the brain, it can widely contribute in many medical operations. With the development of advanced machines and human knowledge of neuroscience, there has been research aimed at directly interpreting brain signals to bridge the activities of the human brain and external behavior. If certain groups of brain signals can be translated into behavioral commands such as "Speak", "Stand up" and "move" simultaneously when detected, it would be possible to instantly translate human thoughts into language and machine commands.

For the realization of a computer and brain interface, it is very essential to gather data that can accurately and comprehensively represent brain activity. Even smallest brain waves should be considered into analysis to capture the features of each mental fluctuation. With Advancement in the technology, there are many tools to measure brain functionality from various aspects, which includes neural signal analysis, brain structural analysis, and blood flow, and plentyadvanced tools are developed to enhancecomputer and brain interface function, including MRI, MEG and EEG [1][2], among which Electroencephalography (EEG) stands out due to its affordability (cheap when compared with other brain functionality detection tools), portability (easy to configure and setup), high accuracy. EEG is an electrophysiological method of monitoring that records the electrical activity of human brain. It is usually not harmful by any way and it is only associate with the electrodes placed on the scalp of the patients. Because of having many advantages over other techniques, EEG has been used widely among neuroscience experiments and studies, and hence a huge amount of data has been accumulated. However, EEG signal interpretation can be complex due to the relatively high signal-to-noise ratio and spatial-temporal complexities inherent in EEG data. In addition, for the practical application of EEG signal interpretations, automatic real time interpretation is required due to the high cost and limited availability of interpretations by trained experts.

The comparatively huge amount of EEG data and the complex spatial- temporal features in EEG signals have introduced and enhanced the usage of artificial intelligence in the field of EEG signal interpretation. The analysis of EEG signals is considered as a classification machine learning problem, where input of different periods of EEG signal corresponds to labels. Various machine learning algorithm, like support common spatial pattern (CSP) [3], vector machines (SVM) [4], ensemble random forests [5] and bagging-boosting algorithms [6]has been studiedwith different EEG datasets in many researches. However, these methods only focus on manually engineering features using the various signal filters mentioned above and do not necessarily provide enough features to train machine learning classifiers to achieve satisfactory classification accuracy.However, this research fails to provide sufficient feature for training machine learning classification with accuracy and low true positive rate.

Deep learning advances in many other areas such as image processing [7] and sentiment analysis [8], financial domain like stock market research [9], medical operations and diagnosis [10], military application [11], fraud detections[12] motivated the application of deep learning in the EEG classification. Many early researchesupdate the traditional signal processing modules with artificial neural networks for automation in the EEG classification using machine learning algorithms. However, this breaks down the machine learning framework integrity, as XGBoost classifier and artificial neural network are trained independently, which can lead to a decrease in the accuracy for EEG datasets. Recent researches integrate the deep learning model with the classification model to gain the high accuracy.

Rajendra [13] in his research used a 13-layered convolutional neural network (CNN) to classify the data into 3 classes as normal, preictal, and seizure EEG signals, and the results analysis shows the improvement in the classification accuracy to 88%. The recurrent neural-network approach was appliedon the energy signals collected form the extraction of the EEG using sleep stage classification [14], result analysis shows that the proposed algorithm enhances the classification accuracy for sleep stage data set analysis. Few researchers also integrated the long-short-term memory with the convolutional neural network for depressed signal detection [15], this integrated model shows the improvement in the classification accuracy.

In the existing literature, performance of the deep learning algorithm on the raw EEG data is not studied enough to understand its impact in the analysis of human brain functions. In the proposed research, we have investigated various deep learning neural network models that focus on spatiotemporal, temporal and spatial feature extraction technique and analyzed its accuracy for emotional EEG dataset. In the proposed research, we also focused on pre-processing of raw EEG datasets that generates inputs for deep neural networks and neural network architecture. Section IIIrepresents the analysis and comparison of the proposed research with various machine learning algorithm. Section IVrepresents the conclusions proposed research and result analysis.

II. METHODOLOGY

In this research, same dataset is used which is used in the previous research [16], in that 2-class label are provided from the EEG signal and binary classification is applied on the various EEG signal analysis stages. Data is collected from one healthy tester. In this process the tester responds to the motor images by using up, down, left and right arrows. This responds to the motor image is recorded. The responses are recorded with the time interval of 2 seconds.

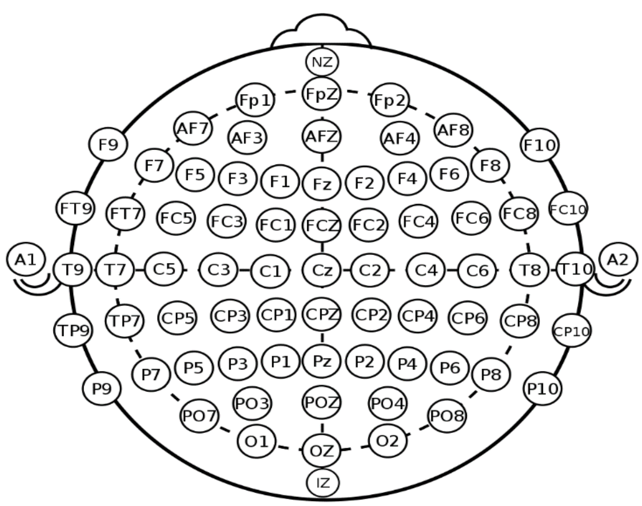

Figure 1: Location of EEG Electrodes

To avoid the issue of data overfitting a well-balanced data set is used with the 1:1 ratio of both the classes. In this experiment, Electrodes are termed as a channel and these electrodes are used to collect the EEG signals. Dataset used in this research contains 59 electrodes. Figure 1 represents the location of EEG Electrodes on the human brain.

Because of the spatial-temporal placement of all electrodes, collects the brain signal at same interval on the same time for all placed electrodes. This spatial correlations between the electrodes enhances the data collection process and hence provide improvement in the training process.

Figure 2 represent the output of EEG signal pre-processing stage, which is present in the form of continuous wave signal which denotes classification label. Figure 2 represent the EEG signal visualization with time series, with the signal frequency of 100 Hz. Using this approximately 1k values from signals are collected every second. This data is combined using spatial and temporal information and then it is collected in the organized manner to send it to the deep learning technique.

In this experiment, sliding window protocol is applied for splitting the training data into fragments of signals on the training input and the output is feed to the deep learning neural network model. For extracting the distinct features present in the fragments, Signals are transformed into fragments. In this experiment the window size of 100 in the sliding window protocol, as the time span of the signal is 2 second.

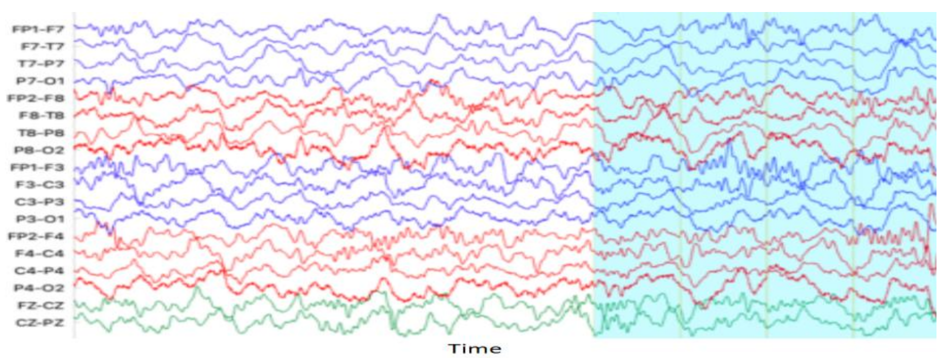

Figure 2: EEG signal visualization with time series

The collected data contains total 200594 data points in the dimension of time. As 100 window size is selected in the sliding window with 10 strides, 20050 trained data are generated. For evaluation of machine learning model accuracy, whole data set is split into 80-20 pattern, where 80% of data is used for training machine learning model, while remaining 20% of data is used to test the trained model.

For the data-preprocessing initially normalization technique is applied on the collected datasets, using this the raw data values gets converted into the standardized range. The standardization is carried out using the equation 1.

$$x\ (stand) = \frac{x - mean\ (x)}{\text{standard deviation } (x)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Using equation 1, data is standardized. The data standardization process ensures that the data is effectively normalized from different dimensions, so that machine learning model can extracts the features from all dimensions.

After this the data is further normalize into the range of 0 to 1.The nomralization is carried out using the equation 2.

$$x\ (Normalized) = \frac{x - minimum\ (x)}{\text{maximum } (x) - minimum\ (x)} \quad \ldots\ldots\ldots\ldots\ldots(2)$$

In this equation minimum(x) and maximum(x) are scalar values. For maintaining the consistency, normalization of testing data is required to be using the statistical values.

III. MODEL ARCHITECTURES

As discussed earlier the data is present in the temporal and spatial dimensions. Spatial data is generated from the signals which are generated from the placed electrodes, and temporal data is a time series data, which is generated over a time. The data present in the temporal information is higher than the spatial information, as the collected data values are higher in temporal dimension than spatial dimension. For reorganization of sequential characteristics from the datasets Recurrent neural networks (RNNs) is designed by flattering the spatial data into vector, EEG dataset samples are reformulated the provided as an input to the recurrent neural network. However, in this process correlation feature of spatial data is lost. Hence in most of the research gated recurrent unit[17] and Long short-term memory [18] are preferred over recurrent neural network. The reason behind not selecting recurrent neural network is gradient vanishing problem, which is observed in RNN.

As the gate structure is added into gated recurrent unit and Long short-term memory, it handles the gradient vanishing problem and itstabilizes the performance of the system.Long short-term memory has 3 gate units which are forget, output and input, while gated recurrent unit has 2 gate units. In Long short-term memory, memory cells are present, while in gated recurrent unit result is pass directly from hidden state to next phase. In this research Long short-term memory and gated recurrent unit is studied to analyses the performance with collected datasets.

Convolutional neural network is mostly used in the image processing, however in this research we have used convolutional neural network for EEG signals classification. Figure 3 illustrates the basic architecture of the convolutional neural network. Kernels and filters are major component of convolutional neural network as it extracts the spatial feature from the provided input data. Figure 3 shows the major component used in the proposed architecture which are batch normalization layer [19], max pooling layer [20] and 2-dimensional convolutional layer with ReLU activation function [21]. Layers present on the low-level module handles the local information collected from the input while layers present on the high-level module handles the processing of the extracted features and focuses on the global feature.

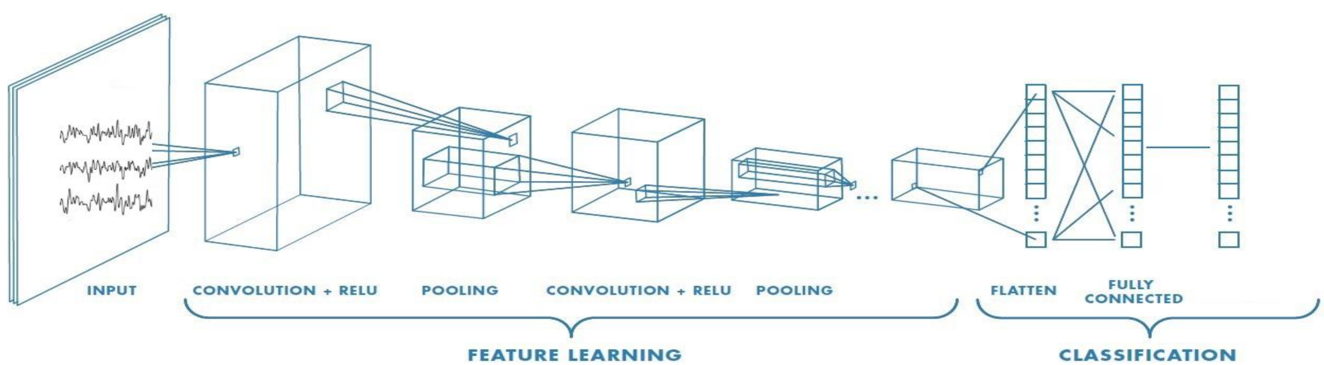

Figure 3: Architecture of the Convolutional Neural Network

After this, the extracted features are flattened and then for classification purpose forwarded to the fully connected network. The input to the neural network in preprocessed EEG data and output is the classification labels. The data sample has a size of 9 x 11 x 100, where 100 is the temporal dimension. This data is sent to the 2-dimensional convolutional neural network. The purpose of using convolutional neural network is to analyze the correlation in the dimension of time by using the convolutional operation on the formulated dataset.

In this research, binary cross-entropy loss [22] is considered for all studied architecture. In this research initial learning rate is fixed to 0.001, hyper parameter tuning is performed using 5 learning rates and 4 filters to compute the optimum combination of the performance. The batch size of 32 is applied. From the result analysis it is observed that the performance accuracy is inversely proportional to the learning rate, however the filter size and count does not affect the performance. The model shows more stable performance at the 0.001 learning rate.

IV. EXPERIMENT RESULTS

For evaluation of machine learning model accuracy, whole data set is split into 80-20 pattern, where 80% of data is used for training machine learning model, while remaining 20% of data is used to test the trained model. This experiment result can suggest the best machine learning algorithm for model formation with the collected dataset. To analyses how well the model is fitting the training data, training loss curves is tested on Gated Recurrent Unit, Long Short-term Memory and 2-dimensional convolutional neural network. Chart1 shows the training loss curves comparison of machine learning algorithm. It was observed that 2-dimensional convolutional neural network performed better than other algorithms.

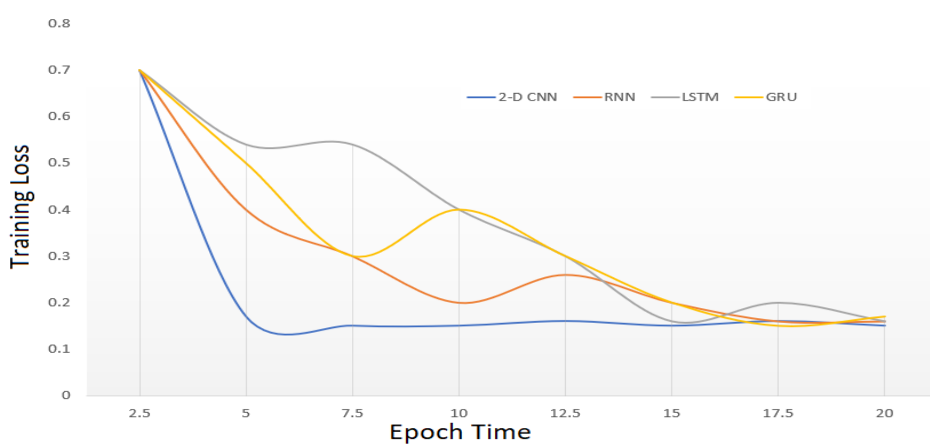

Chart1: Training loss curves comparison

To analyses the performance of the training model, accuracy of the model is an important aspect. In this section accuracy of different machine learning model is studied. Data splitting approach is used to perform the accuracy analysis test. From the result it is observed that 2-dimensional convolutional neural network outperformRecurrent Neural Networks, Gated Recurrent Unit and Long Short-term Memory. 2-dimensional convolutional neural network shows the accuracy rate of 97.65%. Because of complex structure of Recurrent Neural Networks, gradient vanishing problem reduces the accuracy. In case of Gated Recurrent Unit and Long Short-term Memory, even though having advanced architecture with gates, gradient vanishing problem is still observed. Hence 2-D convolutional neural network outperformthis machine learning algorithms.

Algorithm	**Total Instances**	**Accurate Instances**	**Percentage**
Recurrent Neural Network	1000	789	78.9%
Gated Recurrent Unit	1000	897	89.7%
Long Short-term Memory	1000	910	91%
2-D convolutional neural network	1000	976	97.6%

Table 1: Accuracy Rate comparison of ML algorithms

Overfitting is a concept in data science, which occurs when a statistical model fits exactly against its training data, because of this model shows high performance in testing phase, however for unseen or real time data the accuracy for model falls gradually. Hence for performance analysis of data overfiring test, 200 new unseen samples were collected, and the accuracy is validated for this unseen dataset. Chart 2 shows the comparison of accuracy analysis with split validation test and test carried out on the unseen real time dataset.

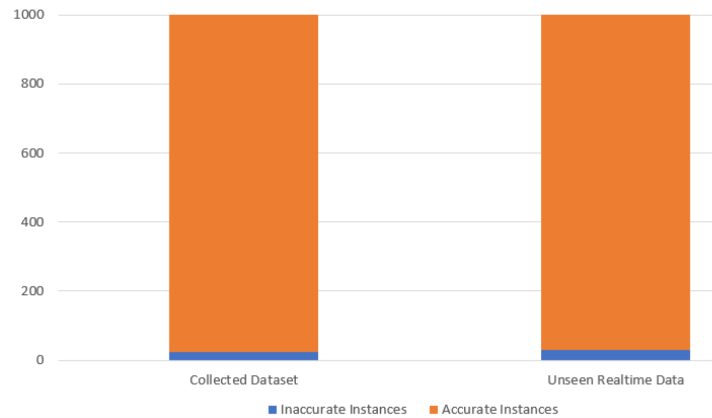

Chart 2: Comparison of Accuracy analysis with Unseen Dataset

Experiment result shows that 2-dimensional convolutional neural network shows better performance in the training loss curve, accuracy rate and accuracy with unseen data.

V. CONCLUSION

EEG signal interpretation can be complex due to the relatively high signal-to-noise ratio and spatial-temporal complexities inherent in EEG data. In this research an EEG data is collected and proper data pre-processing techniques including normalization and standardization are applied. In this research sliding window protocol with specified window size is used for generation of training data for deep learning network. To avoid the issue of data overfitting a well-balanced data set is used with the 1:1 ratio of both the classes. In this research the accuracy of 2-D convolutional neural network with activation function is compared with Recurrent Neural Networks, Gated Recurrent Unit, Long Short-term Memory.

Experiment analysis shows that the accuracy of convolutional neural network has highest accuracy rate of 97.65% among all. Also, it was observed that the convolutional neural network shows better performance in the training loss curve, accuracy rate and accuracy with unseen data.

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