Emotion based Sentiment analysis for EEG signals using deep learning

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Abstract: Speech recognition, the evaluation of extension and flexion, the analysis of Electrooculogram (EOG), and the recording of face movements are some methods that may be used to accomplish emotion recognition. These sorts of emotion identification algorithms, however, are not able to identify human emotion very well since people have the ability to mask their true feelings via speech and fake body language. In this study, we proposed a Recurrent Neural Network and Long Short-Term Memory (RNN-SLTM) based hybrid classification algorithm for emotion classification on brain signals. Various machine learning and Deep Learning classification algorithm have been used for identifying the class sentiment. The Weka 3.7 machine learning framework for machine learning algorithms while DeepLearning4J for deep learning classifier has been used during the implementation. In extensive experimental analysis, the module has evaluated all machine learning classifiers and our proposed hybrid classifier. As a result, the proposed hybrid classifiers obtain the highest accuracy over conventional machine algorithms, around 94% for different cross-validation.
Keywords: Sentiment analysis, social data analytics, brain signal analysis, supervised classification, machine learning, deep learning

DOI Number: 10.48047/nq.2022.20.19.NQ99229 **NeuroQuantology2022;20(19): 2683-2697**

1. Introduction

Nowadays, the topic of Brain Computer Interaction (BCI) embraces everything we do with computers. It allows the human brain to communicate with electrical equipment such as a computer and a mobile phone. BCI has made a significant contribution to the aid of impaired persons. A user interacts with the hardware, which also uses other technologies such as EEG-based BCI framework. Several processing stages were required in the earlier expandable BCI to determine the explanation for brain signals and transform them into something the user wished to accomplish. BCI approaches capture signals from brain tissue, learn about them, and utilize that knowledge to determine the subject's intentions. Electrodes, like those used in imaging investigations, may be utilized for non-medical reasons such as sports, education, tracking, and entertainment. Feelings have a vital role in human cognition, particularly in rational decision-making and interpretation, as well as in assisting individuals in communicating and comprehending. Affects-related computing, which links emotions and systems with human computer Interface (HCI) and other domains of computing, looks to have caught up to HCI recently. Consumer involvement with technology is determined by measuring emotional states utilizing HCI. People, especially for their emotional memories, may experience an emotional awareness of anything other than a response to stimuli in their body. Psychology, neurology, and computer science are all working together to better emotion recognition analysis. Current military, manufacturing, and academia have always exhibited and

fantasized on computer screens, curious to discover how the algorithms of modern artificial intelligence may be applied to any type of modern civilization. Alternative tactics include those that use extra characteristics, such as gut emotions and vague sentiments, as well as facial and vocal signals, including movement and tone of voice, as well as those that employ less certain indications like gut feelings and hazy feelings as identifiers. Biological activity, as well as electrochemical and/or electrical signals, are often recorded using noninvasive sensors. Measurements of conductivity, electrocardiogram, and electroencephalogram are included in these models.
The conventional machine learning algorithms has a general drawback in the feature extraction process. This process is generally awkward and mostly depend on individual professional. An end-to-end Deep learning methods developed as a useful technique to deal with this drawback. In this paper we proposed Recurrent Neural Network and Long Short-Term memory (RNN-SLTM) based hybrid classification algorithm for emotion classification on brain signals.

Deep Learning is a sub-branch of machine learning that enables computers to learn from their prior experiences and comprehend real-world ideas. Machines acquire information from real-world experience and enhance their decision-making abilities as a result of this process [1]. The term "deep" in Deep Learning refers to the number of hidden layers in Neural Networks. Any significant amount of labelled data may be used to train Deep Learning models. Deep learning algorithms are utilized to analyze image sentiment and provide the best results. Deep learning is important for image sentiment analysis since it allows for the use of several techniques such as Convolutional Neural Networks, Deep Neural Networks, Region Neural Networks, and Deep Belief Networks to get the best results [2]. The main issue arises when we encounter contradictory emotions that are expressed via image and word.

The Key Contribution of the proposed method is to extract heterogeneous features from brain signals for achieving better accuracy. The proposed system developed the hybrid deep convolutional neural network for classification of sentiment on real time dataset. The proposed system is validated with synthetic as well as real time dataset for sentiment classification. Furthermore, the presented methodology gives an additional significant classification.

The rest of the paper is laid out as follows: Section 2 provides a short summary of recent research, section 3 describes proposed work, section 4 discusses results , Discussion in section 5 and section 6 concludes the paper.

2. Literature Review

Various signal processing and machine-learning approaches have been used in a variety of seizure identification investigations. The authors of [1] used the wavelet transform (WT) to breakdown an electroencephalogram signal into its frequencies and extract the correlation dimension, standard deviation, and greatest Lyapunov exponent, which are three different aspects of the signals. Different approaches are used to classify epileptic episodes, with the wavelet-chaos-neural network approach showing promising results. In [2,] the fast Fourier transform (FFT) was used to extract features, and a decision tree classifier was used to categorize them. On numerous linear and non-linear algorithms, the research [3] used two separate approaches: principal component analysis (PCA) and genetic algorithm (GA). When compared to a genetic algorithm, using principal component analysis on a non-linear method gave superior results. A survey of wavelet-based techniques to identify epileptic seizures was illustrated in [4]. A strategy that uses training and testing sets to categorize and identify non-seizure and seizure electroencephalogram data by extracting higher-order spectral properties for classification purposes, the support vector machine (SVM) suggested in [5].

EEG data were analyzed using empirical mode decomposition, according to [6]. The intrinsic mode functions were extracted using the Hilbert–Huang transform (HHT). These functions were used to distinguish EEG waves as characteristics. [7] examined sets of ECG time series and compared brain activity utilizing separate brain areas. The analysis of EEG data was accomplished in [8] employing non-linear dynamics of EEG signals characterized by correlation coefficients and greatest Lyapunov exponent, as well as wavelet-based approach. According to [9], for identifying seizures from EEG data, logistic model trees that incorporate statistical characteristics based on an optimum allocation technique are described. EEG data were analyzed for statistical characteristics, which were then used as input into a logistic model tree (LMT) for epileptic seizure detection. These developed models' accuracies are significant performance criteria of the designed systems. The EEG signals were split into frequency sub-bands in a work [10] that employed the discrete wavelet transform (DWT) to extract statistical characteristics. For data size reduction, PCA, independent components analysis (ICA), and linear discriminant analysis (LDA) were used. SVM was used to distinguish epileptic seizures from non-epileptic seizures using the characteristics acquired.

Universum data points were formed in [11] by selecting Universum from a collection of EEG signals known as inter-ictal EEG signals. The authors of [11] achieved seizure classification using feature extraction approaches and Universum SVM. Using neighborhood component analysis, a collection of important characteristics was identified from EEG data in [12]. SVM, AdaBoost (adaptive boosting), K-NN, and random forest classifiers were used to evaluate the system's performance. According to [13,14], the EEG signals were analyzed using convolutional neural networks (CNNs). The CNN model was used to extract characteristics, which were then used to classify the subjects into normal, preictal, and seizure categories.

For the identification of real-time seizures from intracranial EEG signals, the studies [15,16] employed a machine learning technique. The scientists took spectral and temporal properties from the data and used them to train the pattern recognition component. According to [17], the seizure signals were classified using linear discriminant analysis, triadic wavelet decomposition-based features, and K-NN classifiers. The primary goal of this study is to identify epilepsy-related seizures. The capacity to identify seizures permits intercession systems to be implemented for a group of individuals who have had no response to surgery or medicine. The above-mentioned systems' topologies are complex, but they essentially consist of feature extraction and classification steps. These two techniques are merged in the body of CNN in this work to detect seizures from EEG data. CNN is a machine-learning approach based on learning representation, in which the framework learns and determines the characteristics necessary for detection from the several layers that analyze input datasets [18]. In image and audio identification tasks, deep learning has officially shown its capability and beat human reasoning [18,19]. It has been used in a variety of complicated machine learning applications, including early detection of Alzheimer's illness, detection of chest ailments, and concrete comprehensive strength estimate [20]. A simple feature and stacking Ensembled Expert System for Diagnosis of Parkinson’s Disease proposed by [21]. The performance is compared with the most of the recent classifiers and provides promising results. A hybrid affective model using transfer learning approach for emotion classification utilizing wearable device interlinked with mobile devices proposed by [22]. Their outcomes show that the use of deep learning methods is acceptable, their hybrid deep model shows a with 88.6% accuracy. The authors of [23-27] described various methos for feature selection and classification methods for different applications helps us many implementations of data processing and classification.

Table 1 summarizes various current developments in this subject, including the approaches utilized, datasets used, and research gaps.

Table1. Brief overview of survey

Author (Reference No)	**Method**	**Accuracy**	**Gap Analysis**
Ghosh-Dastidar et al. [28]	Spiking neural network	92.5	There is a drop in accuracy for highly deep neural networks.
Idoko et al. [29]	Fuzzy C- Means	90.0	When many CNNs are utilised, a significant level of temporal complexity is produced.
Chua et al. [30]	Gaussian mixture model	93.1	It is possible for accuracy to be affected while extracting region-based features.
Faust et al. [31]	SVM	93.3	Only a single dataset was utilised, and the ADAM default optimization setting was used, both of which helped to remove features that were important to the operation.
Acharya et al. [32]	SVM-Discrete wavelet transform	96.3	The system is unable to recognise several objects inside a grid, resulting in an accuracy rate drop.
Guo et al. [33]	Genetic Programming-KNN	93.5	It is necessary to use an increasing number of computer resources all at once.
Acharya et al. [34]	Fuzzy Sugeno (Wavelet packet decomposition)	96.7	The generation of facts on text data received the utmost attention; nonetheless, an adequate quantity of high-level characteristics was not produced for little items.
Martis et al. [35]	C4.5 decision tree	95.3	Large amounts of effort and complexity involved if training involves the extraction of unknown sentiments.
Bhattacharyya et al. [36]	Random forest	99.4	Take off the upper edge connections to make the calculations less accurate.
Bhattavharyya et al. [37]	SVM	98.6	Only massive text data may be processed by the system; image, audio, even video sets are not supported.

Sharma et al. [38]	LS-SVM	99.0	No facility for image sentiment classification. It is expected that machine learning algorithms would need a significant amount of processing time.
Ullah et al. [39]	P-1D-CNN	99.6	More effort is put into the generation of corners and the analysis of basic network structures.
Thara et al. [40]	DNN	97.21	There is an API dependence for both the train and test systems. ImageNet's library has eliminated certain realistic features in its models.
Hassan et al. [41]	Complete ensemble empirical mode decomposition	98.67	Low accuarcy on resl time EEG signal dataset
Akyol [42]	Stacking ensemble based deep neural networks	97.17	Model Training and fitting took time
Rahib Abiyev [43]	Deep CNN (10-fold cross-validation)	98.67	Low accuarcy for 5 fld and 15 fold cross validation
Al-Sharhan et al. [44]	GA optimization	98.01	It works tardional optimization techniques
Gupta et al. [45]	FBSE with WMRPE and Regression	98.6	Hybrid feature selection technique ha sused very time consuming
Vipani et al. [46]	Learning vector quantization in addition to the Hilbert transform	89.3	Very much low accuarcy and high error rate.
Sharma et al. [47]	Analagous fourier filters bank	99.0	Accuarcy on selective data samples

3. Proposed System Design

In this investigation, a hybrid kind of deep learning methodology used to design and implement an emotion recognition system. In this paper, we demonstrate how a Convolutional Neural Network and a Long short term memory may collaborate to effectively identify EEG data. The dataset has collcted from www.kaggle.com/datasets/samnikolas/eeg-dataset as synthetci dataset while few real time recors collcted from real EEG sensor. The purpose of our research is to investigate and analyse the efficacy of various deep learning and machine learning algorithms for the classification of EEG data. Our objective is to develop a Convolutional Neural Network method for the purpose of feature extraction by making use of a number of different deep learning framework called DeepLearning4J. Using characteristics extracted from Convolutional Neural Networks, the objective of this research is to provide a technique for the categorization of long-term and short-term memories that may be used for unit testing and training. As a consequence of this, one of our goals is to develop a hybrid deep learning model that is able to forecast and categorise an epileptic state in real time. In order to investigate the whole system using supervised learning strategies in the research that was carried out, the first step was to gather information from the mind in the form of EEG data signals. In order to develop the trained system and extract a wide variety of characteristics from the dataset makes use of both the Recurrent Neural Network (RNN) and the LSTM methods. EEG data will be used in an effort to diagnose epileptic disease as the program's primary focus. Display the effectiveness of the procedure while categorising each piece of input data in the testing system so that it corresponds to its own tag [48,49]. The 5-fold, 10-fold and 15-fold data cross validation has used for data splitting with ratio of 70-30% for training and tetsing respectively (it depend on k values such as k value be 5,10 and 15 etc.) [50].

The accompanying figure1 provides an illustration of the suggested architecture for the system.

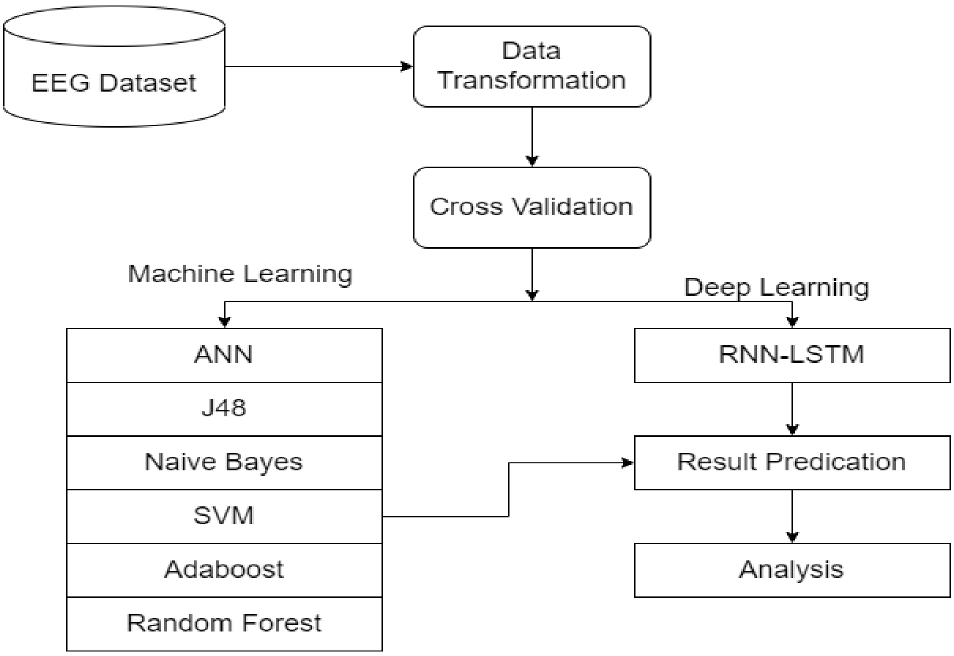

Figure 1. Proposed Systems Architecture for emotion detection using Deep learning

Machine learning classifiers: The Weka 3.7 framework has used for classification of data using machine learning classifies. The different machine learning classifiers has used for entire classification such as NB, SVM, RF, Adaboost, and J48 has used.

Deep learning Classifier (RNN+LSTM)

Deep Learning includes the Recurrent Neural Network (RNN). Too far, RNN has shown to be a highly efficient and successful method of achieving handwriting recognition. Convolutional Neural Networks are neural networks that employ multiple layers of filters to extract information from images [51-55].

RNNs recognize the data's sequential traits and use samples to forecast the next probable state. RNNs if perfectly trained, can develop dependencies within a series of random length [56].
The mapping from inputs $x_{1:T} = (x_1, \dots, x_T)$ to outputs $y_{1:T} = (y_1, \dots, y_T)$

The simple RNN computes the following mapping for t = 1, ..., T as f

$$h_t = \varphi_h(w_h h_{t-1} + w_x x_t + b_h)$$

$$h_t = \varphi_y(w_y h_t + b_y)$$

The network parameters are $\theta = \langle w_h w_x w_y b_h b_y \rangle, \varphi_h$ *and* φ_y are the non-linear activation functions for the hidden state h_t and the output y_t, respectively. For t = 1 the convention is to set $h_0 = 0$ so that $h_1 = \varphi_h(w_2 + b_h)$; alternatively, h_0 can also be added to θ as a learnable parameter [57].

The convolutional layer is the foundation for constructing a RNN model. This layer conducted mathematical calculations on the image that was used as input, as well as resizing the image into the M* M format. This layer's output describes the image's features, such as edge and corner mapping, also known as a feature map. The information was then added to the following layer. The next layer, Pooling Layer is the layer that connects the convolutional and fully connected layers. This layer is used to decrease the network's parameters and computation. The maxpooling and average pooling methods are provided by this layer. The most frequent method is max pooling. The output of the preceding layer, the pooling layer, is sent to the fully connected layer. This layer is where the categorization process takes place.

In practice, input is given through a graphical user interface (GUI). Now, for the GUI, we have built a new file in which we have constructed an interactive window in which we can draw characters on the canvas and identify them using buttons. The Tkinter package for Python was used to create the GUI. Tkinter is a standard Python GUI library. It allows you to build a GUI application quickly and easily. After giving the input, the model is loaded and stored, and predictions are made. The supplied information is progressed further in order to resize in a certain format in order to get the real forecast. The resize image is then passed on to the prediction model, where the provided input's features are extracted. The modelling then yields a prediction, which reflects the likelihood of the target variable based on the assessed importance of the input variables.

Algorithm Design

Input: Normalized training dataset *Train_Data[],* Normalized testing dataset *Test_Data[]*, defined threshold *qTh*

Output: Result set as output with *{Predicted_class, weight}*

Step 1: Read all test data from *Test_Data[]* using below function for validating to training rules, the data is normalized and transformed according to algorithms requirements

$$\text{test\_Feature(data)} = \sum_{m=1}^{n} (.\ \text{Attribute\_Set}[A[m] \ldots\ldots A[n] \leftarrow \mathit{Test\_Data})$$

Step 2 : select the features from extracted attributes set of test_Feature(data) and generate feature map using below function.

$$\text{Test\_FeatureMap } [t........n] = \sum_{x=1}^{n}(t) \leftarrow \text{test\_Feature}(x)$$

$\text{Test\_FeatureMap } [x]$ are the selected features in pooling layer. The convolutional layer extracts the features from input and passes to pooling layer and those selected features are stored in *Test_FeatureMap*

Step 3: Now read entire taring dataset to build the hidden layer for classification of entire test data in sense layer,

$$\text{train\_Feature(data)} = \sum_{m=1}^{n} (.\ \text{Attribute\_Set}[A[m] \ldots \ldots . . A[n] \leftarrow \mathit{Train\_Data})$$

Step 4 : Generate the training map using below function from input dataset

$$\text{Train\_FeatureMap } [t........n] = \sum_{x=1}^{n}(t) \leftarrow \text{train\_Feature}(x)$$

$\text{Train\_FeatureMap}[t]$ is the hidden layer map that generates feature vector for build the hidden layer. That evaluate the entire test instances with train data.

Step 5 : After generating the feature map we calculate similarity weight for all instances in dense layer between selected features in pooling layer

$$\text{Gen\_weight} = \text{CalcWeight (Test\_FeatureMap} \mid\mid \sum_{i=1}^{n} \text{Train\_FeatureMap}[i])$$

Step 6 : Evaluate the current weight with desired threshold
$\text{if}(\text{Gen\_weight} >= \text{qTh})$
Step 7 : $\text{Out\_List. add } \mathbf{(}\text{trainF. class, weight}\mathbf{)}$
Step 8 : Go to step 1 and continue when Test_Data $== \text{null}$
Step 9 : Return Out_List

The $\mathit{Train\_Feature}[]$ and $\mathit{Test\_Feature}[]$ both requires as input for test classifier when generate similarity score between two input objects. These are two separate attributes which represents the training and testing instance respectively. The Th is the denominator that used for selection of each epoch layer result. The $T[j]$ denotes j^{th} attributes of testing instance while the $T[k]$ depicts k^{th} train attribute information. By using feature selection method, we extract some features from both instances and forward to similarity measurement function which is described in step 5. The number of validates instances by threshold is the dense optimized results by CNN.

4. Result

Extensive experimental study has been carried out in java environment with DeepLearning4J learning framework for deep learning and Weka 3.7 for Machine learning classifiers. Numerous machine learning algorithms as well as deep learning classification algorithm has used on Brain signal dataset. The random forest, SVM, Naive Bayes, J48, ANN and AdaBoost are the machine learning classifier evaluated by using the Weka framework. The deeplearning4j framework has been used for the utilization of recurrent neural networks and LSTM has been used for classification. In the experiment evaluation RNN shows highest accuracy than the conventional machine learning classifier. It provides around 94.00% classification accuracy on different class validation. The below figure 2 to 7 demonstrate the classification accuracy with various conventional machine learning algorithms as well as proposed hybrid deep learning algorithm.

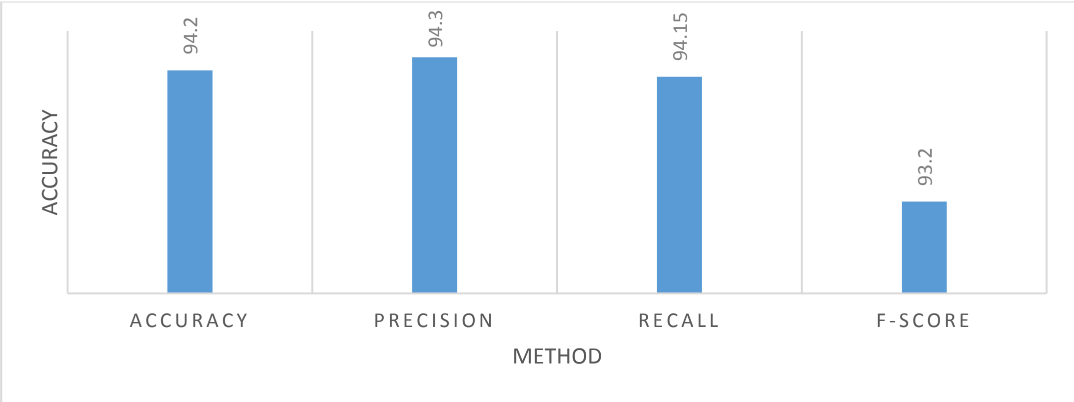

Figure 2: Evaluation of proposed model Using RNN-LSTM with 5-Fold Data Cross Validation (Sigmoid)

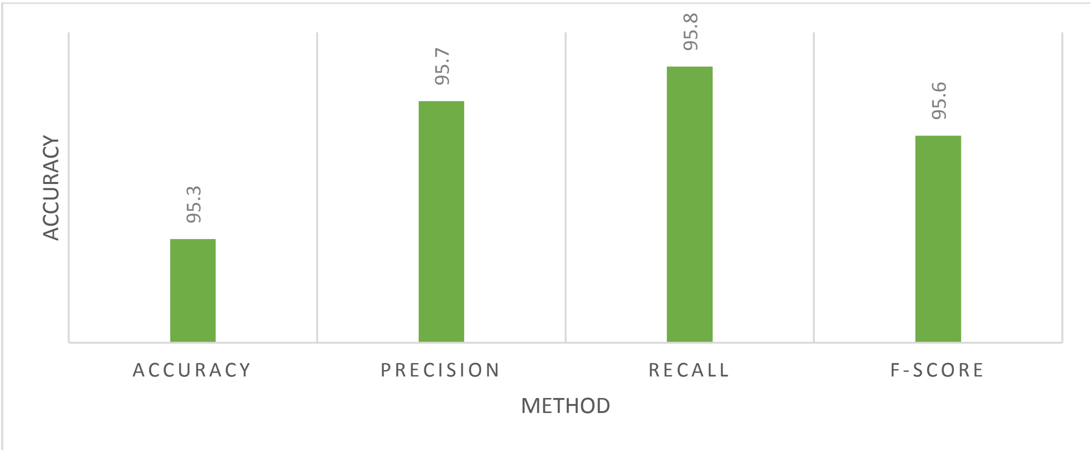

Figure 3: Evaluation of proposed model Using RNN-LSTM with 10-Fold Data Cross Validation (Sigmoid)

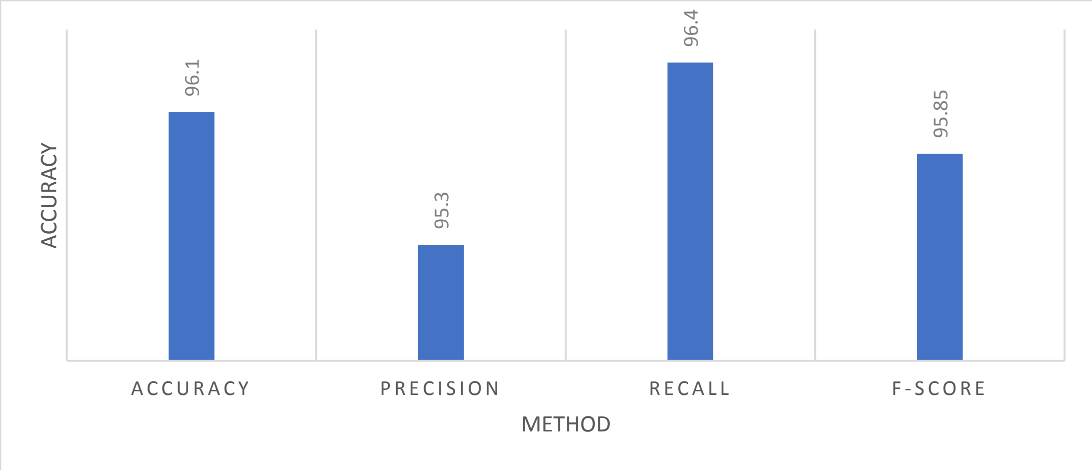

Figure 5: Evaluation of proposed model Using RNN-LSTM with 15-Fold Data Cross Validation (Sigmoid)

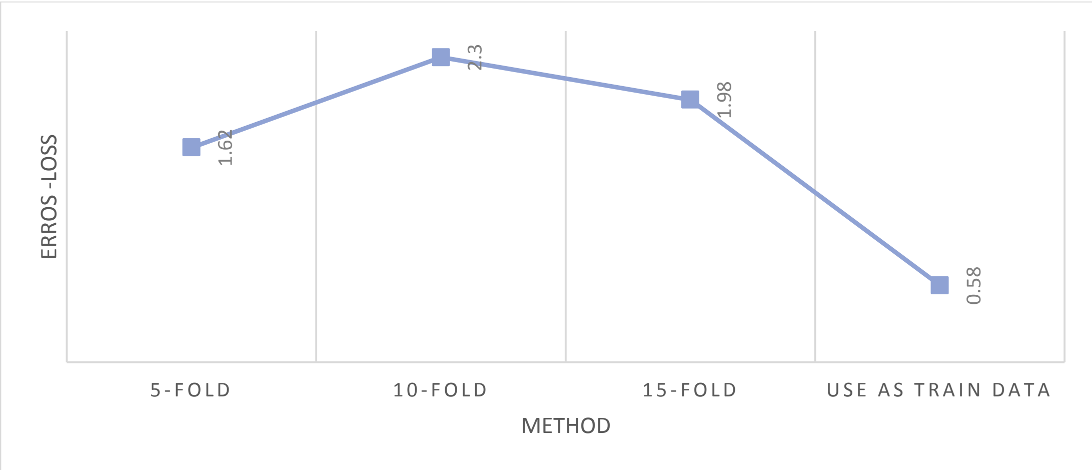

Figure 6 : validation loss of proposed module with different cross validation

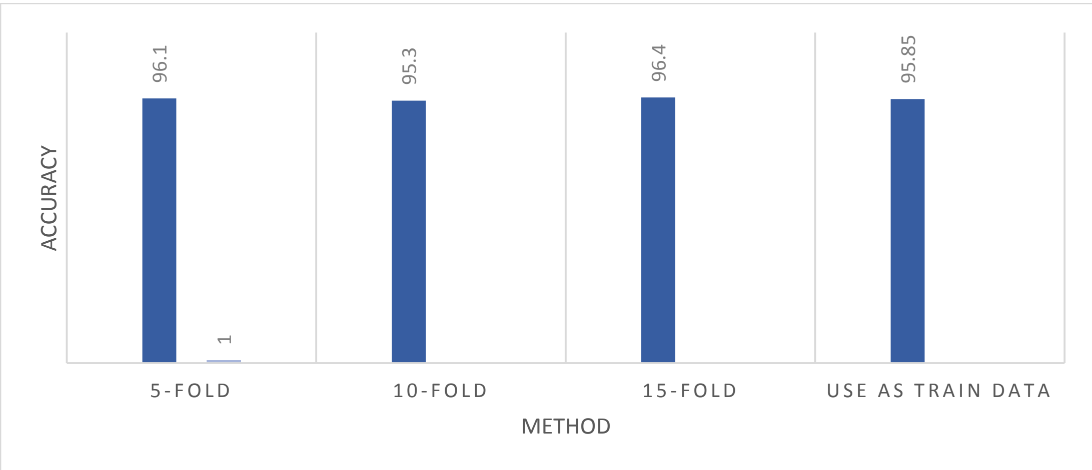

Figure 7 : validation accuracy of proposed module with different cross validation

In the experiment that was just described, the Figures illustrate both the correctness of the testing and the complete loss of the data set. The hybrid technique consisting of a recurrent neural network and an LSTM has been used for identification of sentiment. The pulling layer in the convolutional layer is responsible for the extraction and optimization of a variety of characteristics. The accuracy of the final classification may be predicted using many convolutional layers, followed by the same job and a dense layer. A real-time EEG dataset is able to attain a detection accuracy of 94.00% with the help of the proposed hybrid technique.

The below figure 8 demonstrate the classification accuracy with various conventional machine learning algorithms as well as proposed hybrid deep learning algorithm.

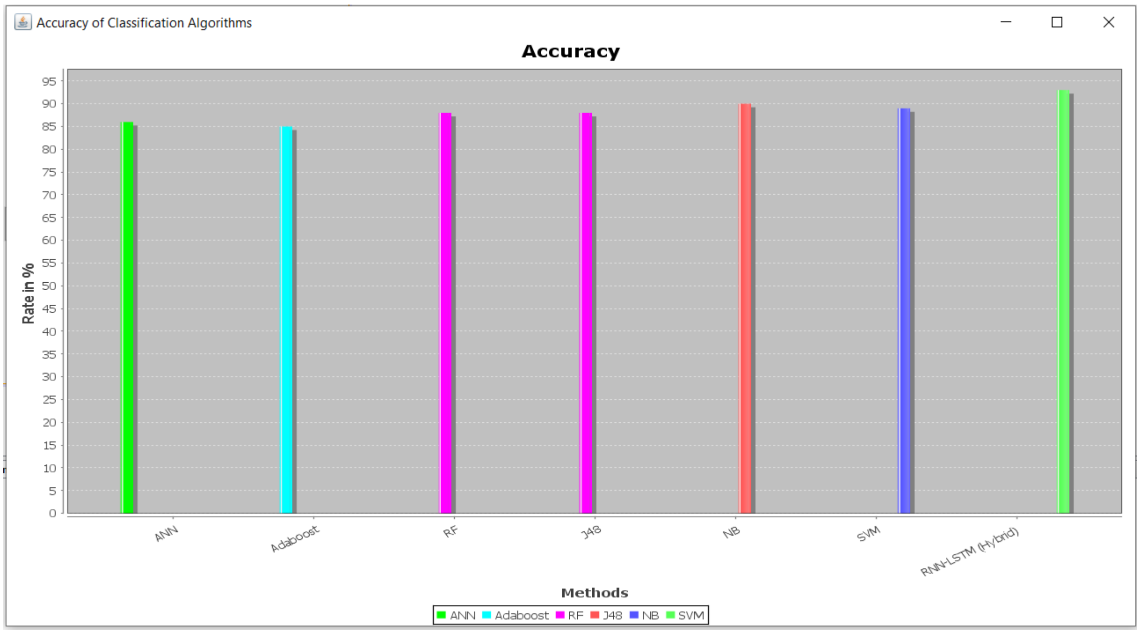

Figure 8 : Classification accuracy of proposed model with conventional machine learning and proposed deep learning classification

5. Discussion

The proposed Recurrent Neural Network and Long Short-Term memory (RNN-SLTM) based hybrid classification algorithm for emotion classification on brain signals provides a significant classification. The experimentation has been done on bith the real time data base as well as dataset collcted from kaggle. The main contribution of the proposed systems is to extract heterogeneous features from brain signals for achieving better accuracy. To develop the hybrid deep convolutional neural network for classification of sentiment on real time dataset. And to validate the proposed module with synthetic as well as real time dataset for sentiment classification. The various wide-ranging experimental study has been carried out in java environment with DeepLearning4J learning framework for deep learning and Weka 3.7 for Machine learning classifiers. The proposed hybrid technique consisting of a recurrent neural network and an LSTM has attained accuracy of the final classification accuracy of 94.00%.

The system achieves the acceptable accuracy but still there are few limitations of this research. The main limitation of this system is to handle Noisy data. The signal files contain too much noise, due to hard to extracts all essential features which generates low accuracy problem. Another limitation incurred during experimentation is related to memory. When we feed large data to RNN-LSTM which produces overfitting problem.

6. Conclusion

Within the scope of this study, we suggested an emotion detection and prediction method that makes use of deep learning methodologies. In recent years, the study of electrical brain activity has emerged as a subject of intense interest in the scientific community as a means of elucidating fundamental problems that affect the human brain. Five different models were proposed by us for the prediction of brain signals. Our methods, which are based on the combination of RNN and LSTM, have been shown to have an accuracy rate of 94.00%, according to the findings. In the future, physicians will be able to further improve seizure prediction in order to strengthen its accuracy, which will enable them to plan treatment more swiftly and correctly. As a consequence of this, more research may be done in order to reduce the total number of components. The scope of this research might be broadened by merging EEG and ECG data, improving classification methods, and using more straightforward techniques for feature extraction.

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