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Deep Learning Is Utilized To Do Sentiment Analysis On EEG Signals Based On Emotions

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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 of the 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 we proposed Recurrent Neural Network and Long Short-Term memory (RNN-SLTM) based hybrid classification algorithm for emotion classification on brain signals. The various machine learning and single deep learning classification algorithm has used for identify the class sentiment. The Weka 3.7 machine learning framework for machine learning algorithms while DeepLearning4J for deep learning classifies has used during the implementation. In extensive experimental analysis the module has evaluated all machine learning classifies and our proposed hybrid classifier.

Keywords: Sentiment analysis, social data analytics, brain signal analysis, supervised classification, machine learning, deep learning

I. INTRODUCTION

Currently, Brain Computer Interaction (BCI) encompasses all computer-related activities (HCI). It enables the human brain to establish communication with electrical devices such as a computer and a cell phone. BCI has made a substantial contribution to assisting individuals with disabilities. In an EEG-based BCI framework, the user engages with the hardware, which employs other technologies. The earlier expandable BCI involved multiple processing stages to analyse brain signals and convert them into the desired user outcome. Brain-computer interface (BCI) methods extract signals from brain tissue, acquire information from these signals, and employ this knowledge to discern the goals of the individual. Electrodes, similar to those employed in imaging studies, can be utilised for non-medical purposes such as sports, education, tracking, and entertainment. Emotions play a crucial role in human thinking, especially in logical decision-making and understanding, as well as in helping people communicate and understand. Emotion-aware computing, which integrates emotions and systems with human-computer interaction (HCI) and other computing domains, appears to have made significant progress in the field of HCI in recent times. The level of consumer engagement with technology is assessed by assessing emotional states through human-computer interactions. Individuals, particularly when it comes to their emotional memories, may have a heightened emotional consciousness that extends beyond a mere bodily response to stimuli. Psychology, neurology, and computer science collaborate to enhance emotion recognition analysis. [link to a video showcasing the functioning of the brain and cognitive processing] The present military, manufacturing, and academic sectors have consistently demonstrated an interest in and imagined the possibilities of utilising the algorithms of contemporary artificial intelligence in various aspects of current society. Alternative strategies encompass the utilisation of other attributes, such as instinctual emotions and ambiguous sentiments, with facial and verbal cues, including gestures and intonation. Additionally, these techniques may involve the utilisation of less definitive indicators, such as gut instincts and nebulous sensations, as means of identification. Noninvasive sensors are frequently used to monitor biological activity, as well as electrochemical and/or electrical data. These models incorporate measurements of conductivity, electrocardiogram, and electocardiogram.

Overview of Deep learning:

It is a subdivision of machine learning that allows computers to acquire knowledge from past experiences and understand concepts in the actual world. Machines gather data from real-world experience and improve their decision-making capabilities through this process [4]. The term "deep" in Deep Learning specifically refers to the presence of multiple hidden layers in Neural Networks. Deep Learning models can be trained with a substantial quantity of tagged data. Deep learning algorithms are employed to assess the sentiment of images and deliver optimal outcomes. Deep learning is crucial for photo sentiment analysis since it enables the use of several techniques, including Convolutional Neural Networks, Deep Neural Networks, Region Neural Networks, and Deep Belief Networks, to get optimal outcomes[4]. An important problem emerges when we come across conflicting emotions that are conveyed through both images and text [5].

The subsequent sections of the paper are organised as follows: Section 2 presents a concise overview of recent research, section 3 outlines proposed work, section 4 examines observations, section 5 explores research contributions, section 6 delves into applications of BCI sentiment categorization, section 7 analyses future possibilities, and section 8 provides a conclusion. These algorithms can be categorised into two groups: lexicon-based algorithms and machine-learning-based algorithms. Machine learning techniques encompass neural networks, Bayesian networks, support vector machines, naive Bayes, and maximum entropy. Lexicon-based algorithms encompass both semantic and statistical methodologies.

II. LITERATURE SURVEY

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

Table1. Brief overview of survey

Author (Year)	Method	Accuracy	Gap Analysis
Ghosh-Dastidar et al. [1]	Spiking neural network	92.5	There is a drop in accuracy for highly deep neural networks.
Idoko et al. [2]	Fuzzy C-Means	90.0	When many CNNs are utilised, a significant level of temporal complexity is produced.
Chua et al. [3]	Gaussian mixture model	93.1	It is possible for accuracy to be affected while extracting region-based features.
Faust et al. [4]	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. [5]	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. [6]	Genetic Programming-KNN	93.5	It is necessary to use an increasing number of computer resources all at once.
Acharya et al. [7]	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. [8]	C4.5 decision tree	95.3	Large amounts of effort and complexity involved if training involves the extraction of unknown sentiments.
Bhattacharyya et al. [9]	Random forest	99.4	Take off the upper edge connections to make the calculations less accurate.
Bhattavharyya et al. [10]	SVM	98.6	Only massive text data may be processed by the system; image, audio, even video sets are not supported.
Sharma et al. [11]	LS-SVM	99.0	No facility for picture sentiment classification. It is expected that machine learning algorithms would need a significant amount of processing time.
Ullah et al. [12]	P-1D-CNN	99.6	More effort is put into the generation of corners and the analysis of basic network structures.
Thara et al. [13]	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. [14]	Complete ensemble empirical mode decomposition	98.67	Low accuarcy on resl time EEG signal dataset
Akyol [15]	SEA	97.17	Overfitiing problem during module training
Rahib Abiyev [16]	Deep CNN (10-fold cross-validation)	98.67	Low accuarcy for 5 fld and 15 fold cross validation
Al-Sharhan et al. [17]	GA optimization	98.01	It works tardional optimization techniques
Gupta et al. [18]	FBSE with WMRPE and Regression	98.6	Hybrid feature selection technique ha sused very time consuming
Vipani et al. [19]	Learning vector quantization in addition to the Hilbert transform	89.3	Very much low accuarcy and high error rate.
Sharma et al. [20]	Analagous fourier filters bank	99.0	Accuarcy on selective data samples

III. PROPOSED SYSTEM DESIGN

This inquiry will utilise a hybrid deep learning methodology to create and execute an emotion recognition system. This research illustrates the effective collaboration of a Convolutional Neural Network and a Long short term memory in identifying EEG data. Therefore, our research aims to examine and assess the effectiveness of several deep learning (DL) and machine learning (ML) algorithms in categorising EEG data. The aim is to create a Convolutional Neural Network technique using a deep learning framework named DeepLearning4J to extract features. The aim of this study is to develop a method for classifying long-term and short-term memories using features derived from Convolutional Neural Networks. This technique can be applied for unit testing and training purposes. Therefore, our objective is to create a hybrid deep learning (DL) model that can accurately predict and classify an epileptic condition in real-time. To comprehensively examine the entire system utilising supervised learning techniques in the conducted research, the initial phase involved collecting EEG data signals as information from the mind. Seth utilises both the Recurrent Neural Network (RNN) and the LSTM approaches to construct the trained system and extract a diverse range of features from the data. The major objective of the programme is to utilise ECG data for the diagnosis of epileptic illness. Demonstrate the efficacy of the approach by classifying each input data in the testing system with its respective tag.

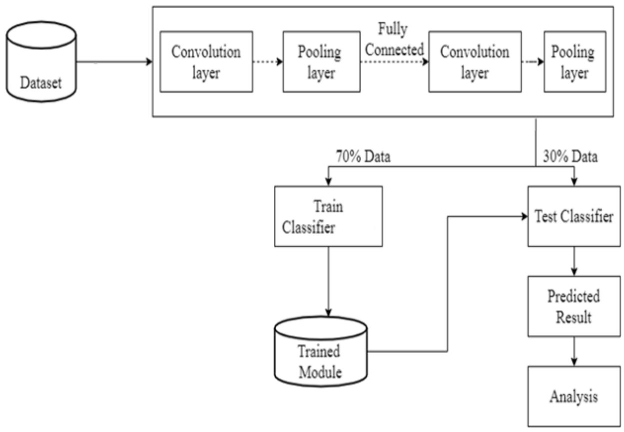

Figure 1: Proposed System Design

Machine learning classifiers: The Weka 3.7 framework is utilised for data classification through machine learning algorithms. Six distinct machine learning classifiers, including NB, SVM, RF, Adaboost, SVM, and J48, were utilised during the complete classification process.

Deep learning Classifier

Deep Learning encompasses the Recurrent Neural Network (RNN). So far, Recurrent Neural Networks (RNN) have demonstrated significant efficiency and success in accomplishing handwriting recognition. Convolutional Neural Networks are a type of neural network that utilise numerous layers of filters to extract information from images.

1: The Convolutional Layer serves as the fundamental building block for generating a Recurrent Neural Network (RNN) model. This layer performed mathematical computations on

the incoming image and resized it to the M * M format. The output of this layer represents the characteristics of the image, such as the mapping of edges and corners, which is also referred to as a feature map. The information was subsequently incorporated into the subsequent layer.
2: Pooling Layer: This layer serves as a connection between the convolutional and fully connected layers. This layer is employed to reduce the number of parameters and computational workload in the network. This layer offers the maxpooling and average pooling techniques. The most commonly used technique is max pooling. The output of the previous layer, known as the pooling layer, is transmitted to the fully linked layer. The categorising process occurs within this layer.
Practically, input is provided via a graphical user interface (GUI). Regarding the graphical user interface (GUI), we have created a new file that contains a window with interactive functionality. This window allows us to put characters on a canvas and identify them using buttons. The Tkinter module in Python was utilised to construct the graphical user interface (GUI). Tkinter is a conventional Python graphical user interface (GUI) module. It enables rapid and effortless development of a graphical user interface (GUI) application. Once the input is provided, the model is loaded and saved, and then predictions are generated. Format in h5. The provided data is further processed to be resized into a specific manner in order to obtain the accurate forecast. The resized image is subsequently forwarded to the prediction model, where the characteristics of the given input are extracted. The modelling process produces a forecast that indicates the probability of the target variable, taking into account the evaluated significance of the input factors.

CONCLUSION

In this paper, we proposed a method for detecting and predicting emotions using deep learning techniques. Recently, the scientific community has become highly interested in studying electrical brain activity as a way to understand fundamental issues that impact the human brain. We offered five distinct models for predicting brain signals. In the future, medical practitioners will enhance seizure prediction to bolster its precision, facilitating prompt and accurate treatment planning. Therefore, additional study may be conducted to decrease the overall quantity of components. To expand the breadth of this research, it could be enhanced by integrating EEG and ECG data, refining classification methods, and employing more simplified ways for feature extraction.

REFERENCES

[1] Ghosh-Dastidar, S.; Adeli, H. Improved spiking neural networks for EEG classification and epilepsy and seizure detection. Integr. Comput. Aided Eng. 2017, 14, 187–212.
[2] Idoko, J.B.; Abiyev, R.H.; Maaitah, M.K.S.; Altiparmak, H. Integrated artificial intelligence algorithm for skin detection. ITM Web Conf. 2018, 16, 02004.
[3]. Chua, K.C.; Chandran, V.; Acharya, U.R.; Lim, C.M. Application of higher order spectra to identify epileptic EEG. J. Med. Syst. 2010, 35, 1563–1571.
[4]. Faust, O.; Acharya, U.R.; Lim, C.M.; Sputh, B.H. Automatic identification of epileptic and background EEG signals using frequency domain parameters. Int. J. Neural Syst. 2010, 20, 159–176.
[5]. Acharya, U.R.; Sree, S.V.; Suri, J.S. Automatic detection of epileptic EEG signals using higher-order cumulants features. Int. J. Neural Syst. 2011, 21, 403–414. \
[6]. Guo, L.; Rivero, D.; Dorado, J.; Munteanu, C.R.; Pazos, A. Automatic feature extraction us-ing genetic programming: An application to epileptic EEG classification. Expert Syst. Appl. 2011, 38, 10425–10436.
[7]. Acharya, U.R.; Sree, S.V.; Ang, P.C.A.; Suri, J.S. Use of principal component analysis for automatic detection of epileptic EEG activities. Expert Syst. Appl. 2012, 39, 9072–9078.
[8]. Martis, R.J.; Acharya, U.R.; Tan, J.H.; Petznick, A.; Yanti, R.; Chua, K.C.; Ng, E.Y.K.; Tong, L. Application of empirical mode decomposition (EMD) for automated detection of epilepsy using EEG signals. Int. J. Neural Syst. 2012, 22, 1250027.
[9]. Bhattacharyya, A.; Pachori, R.B. A multivariate approach for patient-specific EEG seizure detection using empirical wavelet transform. IEEE Trans. Biomed. Eng. 2017, 64, 2003–2015.
[10]. Bhattacharyya, A.; Pachori, R.B.; Upadhyay, A.; Acharya, U.R. Tunable-Q wavelet trans-form based multiscale entropy measure for automated classification of epileptic EEG signals. Appl. Sci. 2017, 7, 385.
[11] Sharma, M.; Pachori, R.B.; Acharya, U.R. A new approach to characterize epileptic seizures using analytic time-frequency flexible wavelet transform dimension. Pattern Recognit. Lett. 2017, 94, 172–179.
[12] Ullah, I.; Hussain, M.; Qazi, E.; Ul, H.; Aboalsamh, H. An automated system for epilepsy

detection using EEG brain signals based on deep learning approach. Expert Syst. Appl. 2018, 107, 61–71.
[13]. Thara, T.D.K.; Prema, P.S.; Xiong, F. Auto-detection of epileptic seizure events using deep neural network with different feature scaling techniques. Pattern Recognit. Lett. 2019, 128, 544–550.
[14]. Hassan, A.R.; Subasi, A.; Zhang, Y. Epilepsy seizure detection using complete ensemble empirical mode decomposition with adaptive noise. Knowl. Based Syst. 2020, 191, 105333.
[15]. Akyol, K. Stacking ensemble based deep neural networks modeling for effective epileptic seizure detection. Expert Syst. Appl. 2020, 148, 113239.
[16] Abiyev R, Arslan M, Idoko JB, Sekeroglu B, Ilhan A. Identification of epileptic eeg signals using convolutional neural networks. Applied Sciences. 2020 Jan;10(12):4089.
[17]. Al-Sharhan, S.; Bimba, A. Adaptive multi-parent crossover GA for feature optimization in epileptic seizure identification. Appl. Soft Comput. J. 2019, 75, 575–587.
[18]. Gupta, V.; Pachori, R.B. Epileptic seizure identification using entropy of FBSE based EEG rhythms. Biomed. Signal Process. Control. 2019, 53, 101569. [CrossRef]
[19]. Vipani, R.; Hore, S.; Basu, S.; Basak, S.; Dutta, S. Identification of Epileptic Seizures Using Hilbert Transform and Learning Vector Quantization Based Classifier. In Proceedings of the IEEE Calcutta Conference (CALCON), Kalkata, India, 2–3 December 2017; pp. 90–94.
[20]. Sharma, M.; Bhurane, A.A.; Acharya, U.R. MMSFL-OWFB: A novel class of orthogonal wavelet filters for epileptic seizure detection. Knowl. Based Syst. 2018, 160, 265–277