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A deep learning-based comparative study to track mental depression from EEG data

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A R T I C L E I N F O

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A B S T R A C T

Background: Modern day's society is engaged in commitment-based and time-bound jobs. This invites tension and mental depression among many people who are not able to cope up with this type of working environment. Cases of mental depression are increasing day by day all over the world. Recently, the onset of the COVID-19 pandemic has added further fuel to the fire. In many countries, the ratio between patients with mental depression and psychiatrists or psychologists is remarkably poor. Under such a situation, the design, and development of an expert system by exploiting the hidden power of various deep learning (DL) and machine learning (ML) techniques can solve the problem up to a greater extent.
Methodology: Each deep learning and machine learning technique has got its advantages and disadvantages to handle different classification problems. In this article four neural network-based deep learning architectures namely MLP, CNN, RNN, RNN with LSTM, and two Supervised Machine Learning Techniques such as SVM and LR are implemented to investigate and compare their suitability to track the mental depression from EEG Data.
Result: Among Neural Network-Based Deep Learning techniques RNN model has achieved the highest accuracy with 97.50% in Training Set and 96.50% in the Testing set respectively. It has been followed with RNN with LSTM model when there were 40% data in the Testing Set. Whereas both the Supervised Machine Learning Models namely SVM and LR have outperformed with 100.00% accuracies in Training Phase and approximately 97.25% accuracies in Testing Phase respectively.
Conclusion: This investigation and comparison-oriented study establish the suitability of RNN, RNN with LSTM, SVM and LR model to track mental depression from EEG data. This type of comparative research using Machine Learning and Deep learning architectures must be framed out on this topic to finalize the design and development of an expert system for the automatic detection of depression from EEG data.

1. Introduction

In modern society, many people must take the challenges to fulfil the objective of their jobs in the stipulated time. As a result, cases of mental depression are rising rapidly all over the globe [1]. In many developed and developing countries, a very large population is experiencing deterioration in mental health conditions [2]. The onset of the COVID-19 Pandemic has added further fuel to the fire [3]. Subsequently, the ratio between the mental patients and the psychiatrist or psychologist has gone down further. Keeping this crisis in mind, scientists, and researchers from all over the world have engaged themselves in finding alternative and automatic techniques to track mental depression, especially from EEG data. Different machine learning and deep learning techniques along with different feature selection methods are getting popularity in this domain.

Wajid Mumtaz and Abdul Qayyum suggested that for automatic detection of unipolar depression, the application of one-dimensional CNN and long and short-term memory (LSTM) can yield an accuracy of 98.32% and 95.97% respectively [4]. Hanshu Cai et al. have implemented 4 basic deep and machine learning techniques (KNN, SVM, CT, and ANN, with 10-fold cross-validation) and claimed that KNN performed best in all datasets with an accuracy of 79.27% [5]. Ayan Seal et al. executed two experiments namely the record-wise split and the subject-wise split and used a DL-based convolutional neural network to track depression using EEG data. They reported a recognition rate of 99.37% and 91.4% respectively [6]. Jing Zhu et al. applied the content-based ensemble method (CBEM) on two different datasets and finally achieved ac-

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curacies of 82.5% and 92.65% respectively [7]. Xiao-Wei Wang, et al. adapted different feature selection methods such as wavelet, power spectrum, nonlinear dynamical analysis and fed the extracted features as the input to the SVM classifier. They observed that an accuracy rate as high as 91.77% can be achieved using Linear Discriminant Analysis (LDA) [8]. Xiaowei Li et al. proposed an innovative approach to track depression from EEG data. Original features were converted into new features by applying the deep forest method and used as input to the SVM classifier. They converted the features into image form by introducing special information of EEG caps to both original and converted features. Finally, the data in image form has been introduced as an input to the CNN classifier. The best recognition rate thus obtained on the ensemble model and power spectral density is 89.02%. CNN is one of the prominent models of deep learning exhibited an accuracy of 84.75% [9]. Natasha P. et al. introduced two different methods of feature extraction namely Discrete Cosine Transformation and Discrete Wave Transformation. Extracted features were treated as input to implement SVM, LDA, KNN, ANN, Naïve Bayes classifier to detect mental stress from EEG data in a better way [10]. Linear features, non-linear features, and power spectral features, etc. were extricated by Ran Bai, et al. to implement six different machine learning techniques such as SVM, KNN, decision tree, Naïve Bayes, random forest, and Logistic Regression. Their outcome showed a higher rate of recall than accuracy [11]. An amalgamated model constructed from CNN and LSTM was used by Betul Ay et al. to obtain better accuracy to track depression from EEG data [12]. Elham S. Salama et al. reported that the 3D CNN model can serve as one of the suitable methods to track emotion from EEG data [13]. A Neural Network-based architecture was implemented by Sana Yasina et al. for the identification of two different types of mental disease from EEG data namely Major Depressive disorder and bipolar disorder. They formulated a review-type research paper by introducing an elaborated discussion on different types of EEG-based protocols, biomarkers, and public datasets for efficient capturing of mental problems. Lastly, some know-how to increase the reliability and performance of proposed methods had been explained in detail [14].

In this article, we have undertaken a comparative study not only to investigate the suitability of different deep learning techniques namely MLP, CNN (MLP has been used as a classifier, but for the sake of brevity only the term CNN will be used throughout the article), RNN, RNN with LSTM, and supervised machine learning algorithms such as SVM and logistic regression to track the mental depression from EEG data but also wish to convey an important message to the world scientists to accelerate and finalize the design and development of expert system (by encouraging more and more this type of comparative studies in this domain which is having societal benefits) that will detect the mental depression of a large population of patients within small span of time. Section 2 will deal with the description of the EEG data set used to undertake this study. A brief discussion on basic methodologies of deep and machine learning will be presented in section 3. Results obtained from the implementation of different classifiers (to undertake an investigation and comparisons) will be presented in section 4. Conclusion and application emerged out from this comparative study will be highlighted in section 5. Conflict of interest is mentioned before Acknowledgments section. Acknowledgments section will acknowledge the assistance so far obtained to carry on this research work. Relevant references consulted during the literature survey of this work will be depicted in References section.

2. Data description

In this research work, we have used the data set named emotions.csv available on the Kaggle website: [21]. This 48.83 MB data contains 2132 rows and 2549 columns. The first 2548 columns contain independent attributes such as mean, standard deviation, Fast Fourier transformation, min and max values, Eigenvalues, entropy, etc. extracted from the EEG brainwave data. The last column represents the dependent attribute named label contains three classes namely positive, negative, and neutral. There are 716 neutral values whereas positive and negative classes each contain 708 values.

3. Methodologies

This section will discuss the six different ML and DL methodologies namely MLP, CNN, RNN, RNN with LSTM, SVM, and LR which are being used successfully as classifiers to solve many real-life problems. A brief discussion on these basic ML and DL methodologies is as follows:

MLP: A multilayer perceptron (MLP) belongs to a class of a feed forward Artificial Neural Network (ANN). A basic MLP architecture is composed of at least three basic layers. 1. the input layer 2. a hidden layer and 3. an output layer. In this architecture, each node uses a non-linear activation function excepting the nodes in the input layer. The data or the inputs are fed to the input layer. The neurons in the input layer propagate the weighted inputs and a randomly selected bias through the hidden layers. Afterwards, a net sum of hidden nodes is estimated to obtain an output response by using a transfer function. In the training phase, the MLP adopts a supervised learning technique termed as back propagation. The multiple layers along with non-linear activation function differentiate the MLP from linear perceptron. As a result, it can handle a data which is not linearly separable [15][17].

CNN: The CNN or ConvNets architecture consists of two main parts feature extraction part and the classification part. Feature extraction is done with the help of convolution layers, and pooling layers to extract relevant features. Feature map thus obtained that provides information about the image such as the corners and edges. There are several types of Pooling operations namely average pooling, max pooling, sum pooling, etc. Features extracted from the pooling layer are flattened and fed to the fully connected layer. Finally, the activation function, such as the ReLU, Softmax, tanH, and the Sigmoid functions are introduced. The activation function is chosen depending upon the specific usage [16,17].

RNN: Recurrent neural network (RNN) is most appropriate for a dataset that carries information represented in terms of time-series or it is sequential nature. This Architecture finds its application in Language Interpreter, Natural Language Processing (NLP), Voice Recognition and Image Captioning, etc. RNN can pull the information from inputs of previous stages and assimilate their impact on the input of the current stage as well as on the output of the present stage. The output of recurrent neural networks depends on information carried by the elements within the sequence. The connection between different nodes forms a directed graph to give a temporal dynamic behavior. This assists to model sequential data which are derived from feedforward networks. It can reduce the complexity of increasing parameters and able to memorize each previous output by introducing each output as input to the next hidden layer. Finally, all the layers are clubbed together to form a single recurrent layer [17].

RNN with LSTM: LSTM is a successor of RNN. RNNs are unable to handle long-term dependencies. Exploding and vanishing of gradients are few other demerits of RNN. Thus, Long- Short-Term-Memory (LSTM) emerged to rectify the deficiencies of RNN. This architecture can deal with continuous and discrete values. The complexity per weight update is O (1) with LSTM. Some fundamental applications of LSTM are namely Time series prediction, Voice recognition, Rhythm Learning, Song Composition, Handwriting Recognition, Human Action Recognition, etc. [18].

Table 1
Training set performance of Different Neural Networks and Supervised Machine Learning architectures with 20%, 30% and 40% data in the Testing Set.

Training set performance of Different Neural Networks and Supervised Machine Learning architectures						
Percentage of data in the Testing set	MLP (Recognition Rate in %)	CNN (Recognition Rate in %)	RNN (Recognition Rate in %)	RNN with LSTM (Recognition Rate in %)	SVM (Recognition Rate in %)	LR (Recognition Rate in %)
20%	83.20	97.36	97.95	97.27	100.0	100.0
30%	84.28	97.36	97.32	93.13	100.0	100.0
40%	84.77	97.27	97.27	96.97	100.0	100.0

Table 2
Testing set performance of Different Neural Networks and Supervised Machine Learning architectures with 20%, 30% and 40% data in the Testing Set.

Testing set performance of Different Neural Networks and Supervised Machine Learning architectures						
Percentage of data in the Testing set	MLP (Recognition Rate in %)	CNN (Recognition Rate in %)	RNN (Recognition Rate in %)	RNN with LSTM (Recognition Rate in %)	SVM (Recognition Rate in %)	LR (Recognition Rate in %)
20%	77.37	59.25	97.95	87.58	97.65	97.18
30%	75.93	56.40	96.40	90.13	97.18	96.87
40%	76.43	49.82	93.90	97.65	95.89	96.60

SVM: The main objective of the SVM algorithm is to generate the best line also called decision boundary which can segregate n-dimensional space into different classes so the new data point can be put in its appropriate class in the future. There can be multiple lines/decision boundaries to segregate the classes in n-dimensional space, but the objective is to find out the best decision boundary that helps to classify the data points. This best boundary is known as the hyperplane of SVM features. It can be applied for both linear classes by using single straight as well as for nonlinear data sets. The data points lie nearest to the hyperplane are called Support Vectors [19].

LR: Logistic Regression falls under the supervised machine-learning technique which outperforms when output features are binary or categorical. It can also be applied successfully when the dependent variable contains more than two categories. It estimates the probabilistic values lying between '0' and '1' by use of a logistic function. Logistic Regression is best suited for the problem of classification, it exploits the concept of probability. Logistic Regression generally uses Sigmoid Function. This algorithm finds its abrupt use in medicine, social science, etc. [20].

4. Results and discussions

We have applied four different deep learning architectures namely MLP, CNN, RNN, RNN with LSTM and two supervised machine learning techniques namely SVM, and LR on the same data set, to investigate and compare the performance of these models to track mental depression from EEG brain wave data. Python programming has been adopted to implement different architectures. Before the implementation of architecture, appropriate codes are used to split the data into training and testing sets. Performance and suitability of these models have investigated by keeping 20%, 30%, and 40% data in the testing sets. Table 1 represent the training data recognition rate in percentage (%) obtained by implementation of these models with keeping 20%, 30% and 40% data in the testing set. Performance of these models further checked also on testing data set and recognition rate thus obtained are depicted in Table 2. It can be noticed from Table 1 that the training set recognition rates of MLP architecture are 83.20%, 84.28%, and 84.77% respectively with keeping 20%, 30%, and 40% data in the testing set. On the other hand, corresponding training set recognition rates (with 20%, 30%, and 40% data in the testing set) for CNN architecture are 97.36%, 97.36%, and 97.27% respectively. Further scrutinization of this table reveals that RNN and RNN with LSTM architectures are also performed well when implemented with 20%, 30%, and 40% data in the testing set. The corresponding training set recognition for these two neural networks-based deep learning architectures are 97.95%, 97.32%, 97.27% (for RNN) and 97.95%, 93.13%, 96.97% (for RNN with LSTM) respectively. Finally, it is really, appreciable to notice that the training set recognition rate is 100% for both the machine learning techniques namely SVM and LR. It remained invariant (100%) for all three combinations of the percentage of data in the testing set i.e., with 20%, 30%, and 40% data in the testing sets.

Now, the test dataset is used to provide an unbiased evaluation of these models fitted on the training dataset. It can be noticed from Table 2, the testing set recognition rates are 77.37%, 75.93%, and 76.43% respectively for MLP architecture. So, it can be concluded that MLP architecture has shown satisfactory performance during its implementation (both in training and testing phases). CNN architecture has shown a noticeable fall in its recognition rate when tested on testing data sets. Here, the testing set recognition rates are 59.25%, 56.40%, and 49.82% respectively. Demonstrates that CNN architecture has performed noticeably well in its training phase whereas underperformed in its testing phase. CNN architecture is not suitable for sequential time series data.

The testing set recognition (with 20%, 30% and 40% data in the testing set) for RNN and RNN with LSTM architectures are 97.95%, 96.40%, 97.65% and 87.58%, 90.13%, 97.65% respectively. Both these neural network-based deep learning architectures have performed remarkably well in their training and testing phases. It is to be noted that in comparison to RNN model, the RNN with LSTM architecture (in testing phase) has experienced about 10% and 6% drop-in recognition rate when there were 20% and 30% data in the testing set respectively whereas the recognition rate (about 97%) is nearly equal both in the cases of RNN and RNN with LSTM model when there were 40% data in testing set. Finally, among neural networks-based deep learning architectures, the RNN model has been found as most suitable to track mental depression from EEG brain wave data. It has been followed with RNN with LSTM model when there were 40% data in the testing set.

The supervised machine learning architectures namely SVM and LR have outperformed both in training and testing phases when implemented to track the mental depression from EEG brain wave

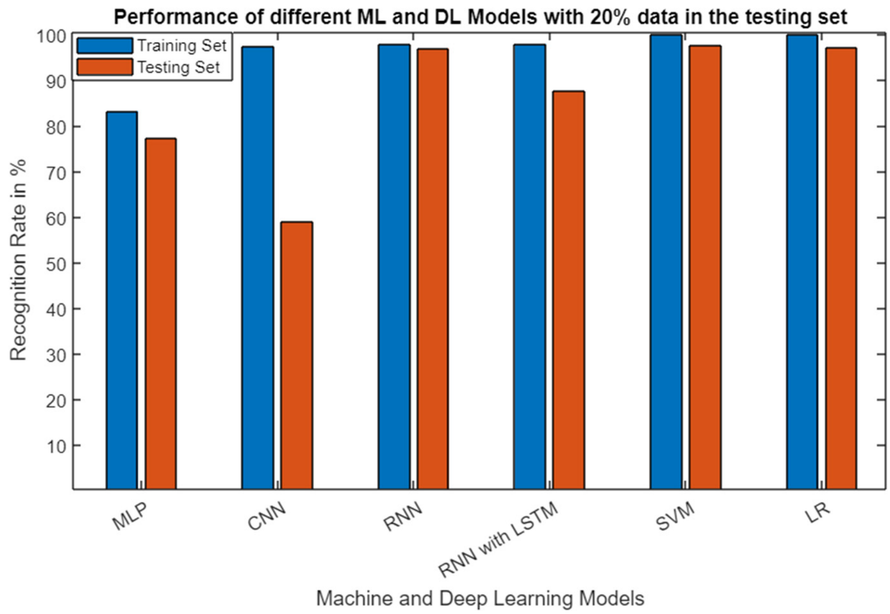

Fig. 1. Performance of Different Neural Networks and Supervised Machine Learning architectures with 20% data in the Testing Set.

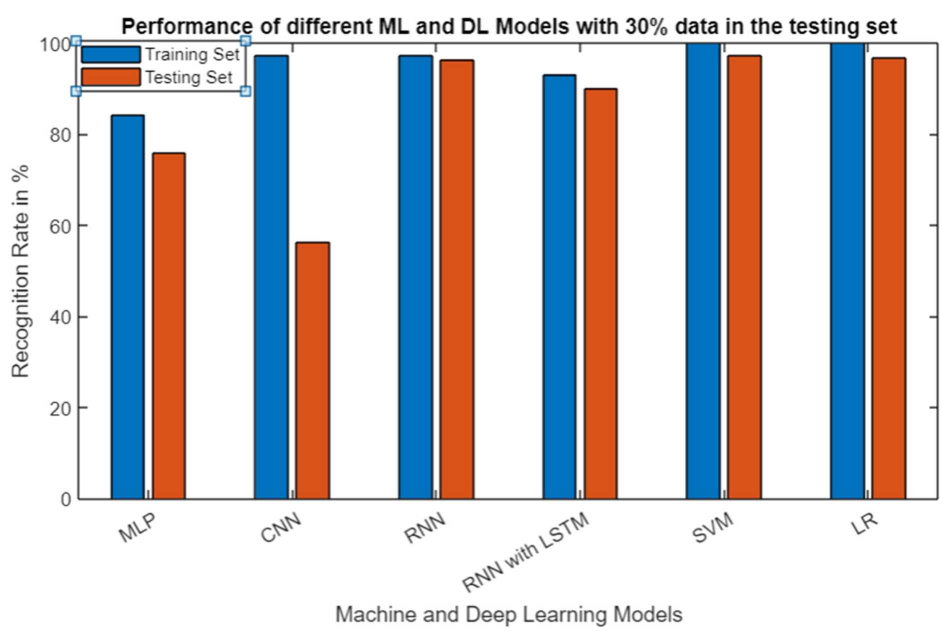

Fig. 2. Performance of Different Neural Networks and Supervised Machine Learning architectures with 30% data in the Testing Set.

data. The relative testing recognition rate for SVM (with 20%, 30% and 40% data in the testing set) and LR (with 20%, 30% and 40% data in the testing set) are 97.65%, 97.18%, 95.89% and 97.18%, 96.87%, 96.60% respectively. SVM and LR models are best suited for sequential and time-series data. Finally, it is to be concluded that SVM and LR architectures have been found most suitable to track mental depression from EEG brain wave data.

From the obtained results, Fig. 1, Fig. 2, and Fig. 3 (bar diagrams) are drawn further to undertake a more clear-cut comparison in the performance of different Deep Learning (Neural Network) and Supervised Machine Learning architectures. Fig. 1 depicts both training and testing recognition rates of MLP, CNN, RNN, RNN with LSTM, SVM, and LR with 20% of the data in the testing set. Similarly, Fig. 2 and Fig. 3 reflect both training and testing recognition rates of MLP, CNN, RNN, RNN with LSTM, SVM, and LR with 30% and 40% of data in the testing set respectively. Scrutinization of these figures once again establishes that among Neural Network-based Deep Learning architectures, the RNN model has been emerged out as the most suitable model to track mental depression from EEG brain wave data as it has performed best both in training and testing phases. It has been followed with RNN with LSTM when there were 40% data in the testing set. Further investigation of these figures reveals that both the Supervised Machine learning techniques (SVM and LR) have performed exceptionally well in both training and testing phases finally proven their suitability to track the mental depression from EEG brain wave data.

5. Conclusion and applications

Considering a leaps and bound rise in the cases of mental depression all over the world the authors have formulated this research article to capture the suitability and unsuitability of dif-

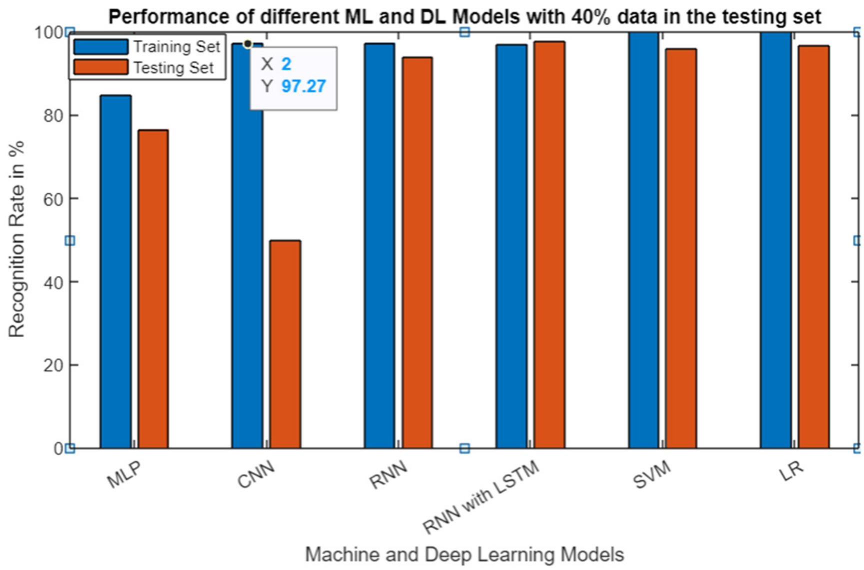

Fig. 3. Performance of Different Neural Networks and Supervised Machine Learning architectures with 40% data in the Testing Set.

ferent neural networks and Supervised Machine learning architectures (MLP, CNN, RNN, RNN with LSTM, SVM, and LR) to detect mental depression from EEG brain wave data. This meaningful application of ML and DL architectures has got tremendous societal benefits. It carries an important message for the researchers and scientists all over the world. They must encourage this type of comparison-based studies on a larger scale to accelerate and then finalize the design and development of an expert system which will detect the depression automatically from the EEG Brainwave data. By doing so a large population of the patients will be able to know on a preliminary basis whether they are suffering from mental depression or not within a very short span of time. It has been concluded that among neural network-based deep learning techniques, the RNN and RNN with LSTM (especially when there were 40% data in testing set) architectures have yield better results (both for the training and testing phases) in comparison to MLP and CNN architectures. This establishes the suitability of RNN and RNN with LSTM architectures when implemented in the case of sequential and time-series data and the EEG brain wave data inherit these properties. Results obtained by the implementation of MLP architecture are moderate (both in training and testing phases) in nature whereas CNN architecture has under-performed especially during the testing phase of the implementation. The CNN architecture is best suited for image data. Generally, the Supervised Machine learning models work well in the case of sequential, linearly separable, and time-series data. This characteristic has been reflected in the result obtained from the implementation of SVM and LR architectures. Both SVM and LR have outperformed (both in training and testing phases) when implemented to track the mental depression from EEG brain wave data. Finally, it can be concluded that RNN, RNN with LSTM (for 40% data in testing set), SVM, and LR can be considered as suitable architectures to track mental depression from EEG brain wave data. Finally, the conclusion is, this type of deep-learning-based automatic depression detection system may be proved extremely useful in tracking mental depression at various psychiatry departments, medical and diagnostic centres, and in different hospitals also.

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Declaration of competing interest

The authors declare they have no conflict of interest for this study.

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This is to be acknowledged that the authors of this research article have used the data set emotions.csv available on the web link referred to as Reference. No. 21. Without the availability of this data set, it was not possible for the authors to undertake this type of comparative research work using different ML and DL models.

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