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DEEP LEARNING APPROACHES FOR CLASSIFYING DATA: A REVIEW

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Abstract

Data mining can be considered as the first approach for classification of sentiments. Data mining can be considered as the first approach for classification of sentiments. Later, Machine learning and its techniques were used to analyse sentiments but, machine language-based learning systems find it complex to understand the language of humans. Therefore, we move towards deep learning models to analyse sentiments. The subgroup of machine learning is Deep-Learning; it involves networks, namely RNN (Recurrent Neural Networks), Recursive Neural Networks, Convolutional Neural Network (CNN) and Deep Belief Networks. Neural networks are very useful in the generation of text, the depiction of vector, word assessment, classifying sentences and representation. Sentiment analysis can be determined as a process for identifying the emotions with the help of a series of words which are used in online sites. It can be utilized to analyse the point of view and attitudes, depending on the words. Sentiment analysis is mostly used in monitoring social media to gain information about public opinion on certain trending topics. Sentiment analysis is performed by taking some sentiment examples, the features are extracted from sentiments and then the parameters are trained in our model and in the final stage, the model is tested. In this paper, an empirical survey of the three models of deep learning, namely RecurrentNN, RecursiveNN and ConvolutionalNN are discussed.

Keywords: Convolution NN, Deep learning, Performance, Recursive NN, RNN, Sentiment analysis.

1. Introduction

The Sentiment analysis can be determined as a process for identifying the emotions with the help of a series of words which are used in online sites. Businesses and organizations get more benefited by sentiment analysis in terms of providing business valuable insights about people's feelings regarding a product or service. It can be utilized to social media channels to recognize the sharp points, by which we can determine potential product advocates or social media influencers [1]. It can also be utilized in the corporate network to analyse potential threats related to business and hence enabling us to be proactive in quickly dealing with it. By applying sentiment analysis to an email server, emails can be monitored for their 'tone.' Though sentiment analysis can be used in different areas, it is often difficult to conclude whether a statement is positive, neutral or negative. Two things that are to be considered are facts and opinions. Opinions are used to express the sentiments and feelings of people towards facts. Random k-Label sets, Multi label k-Nearest Neighbours or Apriori are the data mining algorithms, have been used for classification of sentiments purpose [2]. The need for finding out the feelings and opinion of people has become inevitable with the growth in thought mining and sentiment analysis.

Machine learning and its approaches can be utilized to analyse sentiments but it is difficult for machine-based systems to analyse the natural language [3]. A classifier should be initially trained to process data and generate results. Training data from various sources can be used for this purpose, one popular means is to use an assortment of movie reviews labelled as positive or negative. With a perfect lexicon, a lexicon-based method might be best, but in many cases, especially for social media analytics, dictionaries are not as good as they could be as many of them have not been adapted to the linguistic and para-linguistic features of computer-mediated communication in general or of social media like Twitter and Facebook [4]. Therefore, deep learning could be a more adequate way to classify the sentiments.

Deep learning is much dominant in unsupervised and supervised learning; numerous researches are being done using sentiment analysis with deep learning. It contains several famous and active models which can be used for solving different problems efficiently. Typically, text classification, including sentiment analysis can be performed in one of the two ways: if ample training data is available, supervised learning can be used and unsupervised training followed by a supervised classifier can be used if there are insufficient training facts to train deep neural network prototypes. Deep learning can be defined as a subgroup of machine learning; it involves different types of networks namely RecurrentNN, RecursiveNN and ConvolutionalNN [5], however, a huge amount of data is required for these networks for training. Word2vec and Paragraph vectors are attested to function very well in sentiment analysis for smooth to train and train. In this paper, a survey has been conducted to analyse different types of approaches that are utilized in the classification of texts. In this paper, Section 2 describes the methods of Deep learning, Section 3 gives the experimental details of the deep learning approaches, and Section 4 explains about discussions and ended with conclusion as Section 5.

2. Deep Structured Learning

The subcategory of machine learning is deep learning, which is built depending on a bunch of algorithms that try to prototype high-level abstractions of information with the help of different complex structured layers for processing. Discrete deep structured learning systems such as Recurrent Neural Networks, Recursive Neural Networks, and convolutional Neural Networks and have utilized to areas like speech recognition, voice recognition and bioinformatics in which the models are attested to construct state-of-the-art outcomes on different jobs [6].

2.1. Aims and research

The following are the aims of the research are discussed:

- **A1:** Presenting an empirical survey on the methods of deep learning such as CNN, Recurrent NN and Recursive NN by presenting a brief explanation about all these neural networks.
- **A2:** To design flexible architectures of deep learning for sentiment analysis on different datasets.
- **R1:** Finding the best method of deep learning among CNN, Recurrent NN and Recursive NN by comparative experimental study of all these neural networks by taking the different data set sizes to analyse the sentiments.
- Hypothesis-**H1:** Convolutional Neural networks (CNN) works best with more data points and Recurrent NN and Recursive NN has shorter memory problem.

2.2. Convolutional neural network

CNN is a breed of feed-forward artificial neural network that is the build-up of nerve cells containing weights and biases. Every nerve cell obtains a lot of inputs, calculates the weighted sum, passes it to an activation function and generates an output [7].

Working of CNN

The architecture of CNN is slightly different from regular neural networks. It comprises of input, output and many hidden levels, which are fully connected, normalization levels or convolutional or pooling layers. All these layers of CNN are organized in three magnitudes: depth, height, width. Further, the neuron cells of one layer are associated with a portion of neurons in the next layer, and the result is brought down to a single vector to formulate along the depth dimension.

Convolution is considered as the main building block of CNN. Here, a convolution operation is performed to detect the features, and the results are sent to the next layer. In the CNN, the input layer which accepts the pixels of the image in the form of buffers, the buffer can store the values up to 3-bits, i.e., 23=8 colors (000-black, 111-white, 100-red, 010-green, 001-blue, 110-yellow, 011-cyan, and 101-magenta) and gray scale images as shown in Fig. 1.

If the image having more than 8 colors, then color index is used to store colors. Based on the pixel value, the color values are retrieved from the color index as shown in Fig. 2. Here the pixels as given input i.e. neurons or features to the input layer.

The output dimension after the filter operation on the image is (*height-filter height*+1) (*width-filter width*+1)*1 as shown in Fig. 3.

Different filters can be applied to the image based on the users' requirement such as edge detection, noise reduction, blur and sharpen by applying filters.

Therefore, to perform a convolution operation in CNN, a ‘filter’ is used in addition to input data and the produced set generated is named as ‘feature map.’ The output feature map generated is always smaller than the input [8]. Therefore, to avert the output to shrink, ‘padding’ is used which are nothing but zeros.

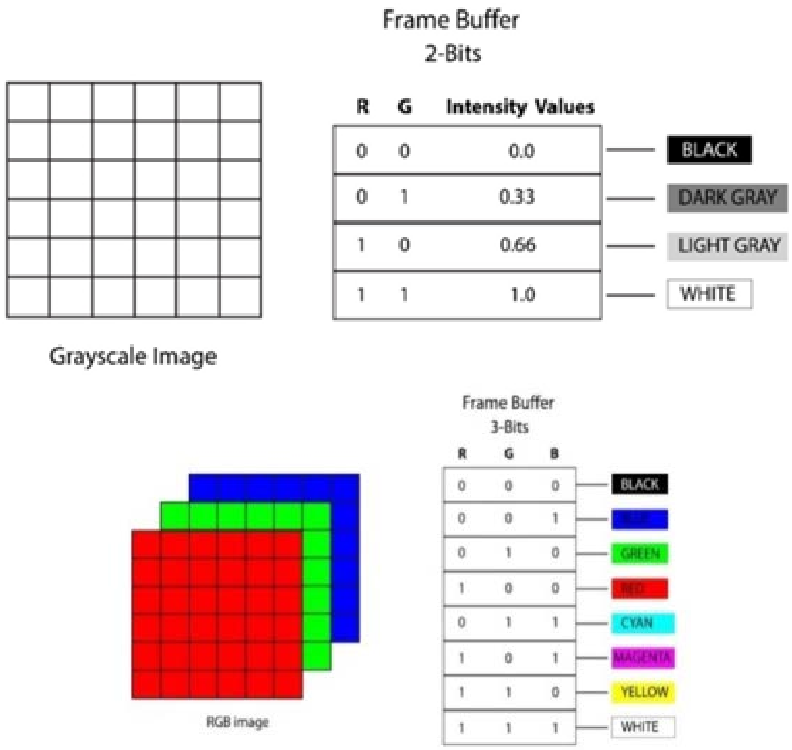

Fig. 1. Gray scale image with frame buffer of size 2 and RGB image with frame buffer of size 3.

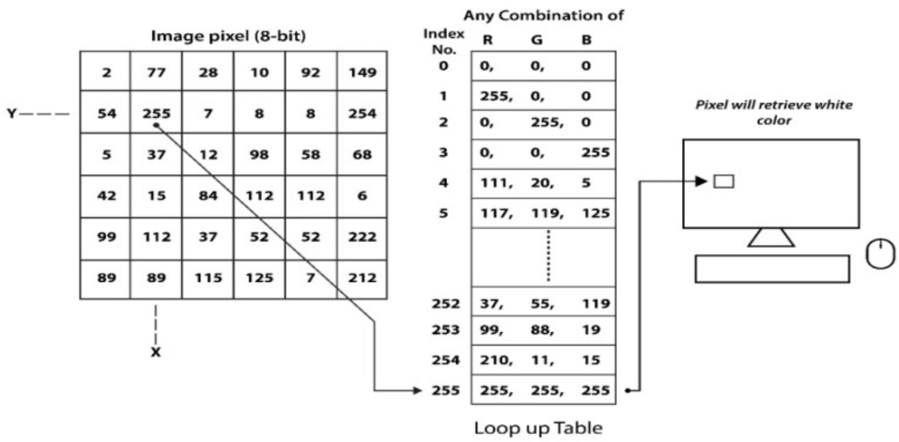

Fig. 2. Indexed color image.

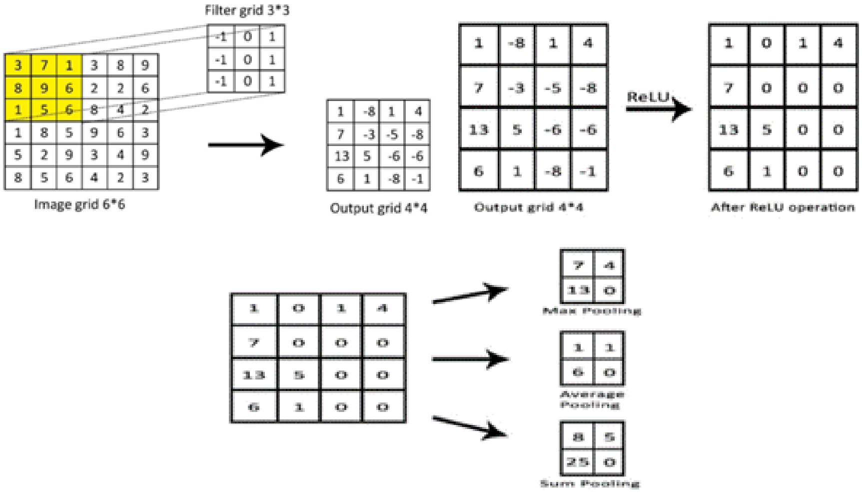

Fig. 3. ReLU activation and pooling applied to generated feature map.

There are many types of activation functions are used on the hidden layers like Binary step, tanh, Sigmoid, linear, ReLU and Leaky ReLU. The activation function is the nonlinear transformation that we do over the input signal. This transformed output is then sent to the next layer of neurons as input. Output for next *layers = Activation (summation of weights of the edges * inputs given at neutrons) +bias*. When ReLU activation function is applied for output grid 4*4, then the values obtained are max (0, value).

Figure 4 illustrates the elementary design of Convolutional Neural Network for analysing sentiments. In this figure, a sentence is given as input to the Convolutional NN model.

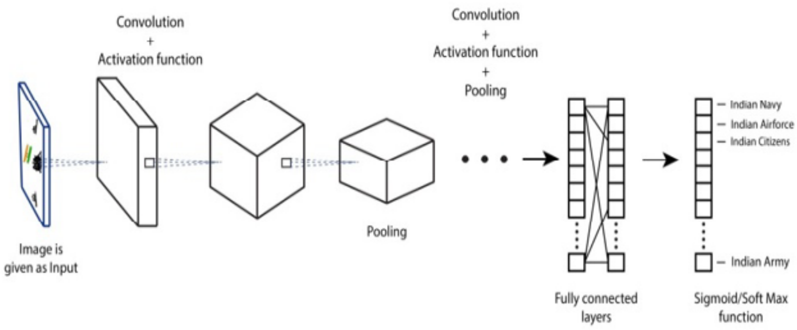

Fig. 4. The basic design of convolutional neural network.

The obtained output is flattened and given as input to a fully connected layer; the output function classifies the given image into the categories.

Kim [9] had experimented with word2vec building on top of CNN regardless of slightly tuning the hyper-parameters, a plain, single convolution layered CNN performs impressively fine. Islam and Zhang [10] projected a novel design of CNN to foresee the visual content sentiments. Caffe and Python are used to implement CNN on a Linux machine and hyper-parameters are used in biases and pre-trained GoogLeNet data is used as weights. A deep CNN model influenced by GoogLeNet has been designed which consists of 22 layers for sentiment analysis. SGD (Stochastic gradient descent) algorithm is used for optimization, in which 60 epochs were used for training the model.

Twitter data set with 1269 images is considered and propagated for the experimental purpose by using Amazon Mechanical Turk (MTurk), labels are given to the images and generation of sentiment tags for every image involved five workers. The evaluation of the designed model on the dataset was achieved and the outcomes show that it achieved great performance compared to the existing models without fine-tuning on Flickr dataset. Nearly 9% progress in the performance was achieved by GoogleNet when compared with AlexNet that was used in previous works. Better feature extraction was achieved by transforming GoogLeNet to visual sentiment analysis framework. The use of hyperparameters helped in achieving a reliable and constant state. In a study by Ouyang et al. [11] a seven-layered framework has been represented for the study of sentence's sentiments. CNN and Word2vec are used to estimate the representation of the vector. Word2vec used to produce word embedding is projected by Google. To improve the generalizability, the correctness of the projected model with the Dropout technology, Normalization and Parametric Rectified Linear Unit (PReLU) is used. The proposed structure was demonstrated with rottentomatoes.com dataset containing movie reviews with five tags. The model when compared with former models such as Matrix-Vector recursive neural network (MV-RNN) and recursive NN outperformed the existing models with the 45.5 % conviction. Severyn and Moshitti [12] proposed a system to analyse twitter sentiments using deep learning, which is essential to train a precise model while preventing to add any additional features. To enhance the regularization of neural networks Dropout technology was used. You et al. [13] stimulated the necessity to control the social multimedia content by utilizing visual and textual SA approaches. The Mechanical Turk (AMT) and intelligence crowd were hired to assign sentiment tags for chosen visual tweets.

Galán-García et al. [14] advanced a classifier to predict the sentiments of Italian Twitter messages. They built up a model based on deep learning in which a large volume of feeble data is influenced to instruct a 2-layer convolutional neural network. Zhang and Chen [15] explored the employment of a convolutional neural network to elicit appropriate components in the absence of the requirement of hand-crafted characteristics. According to the experiments, CNN can be an efficient model for Spanish tweets SA. The proposed CNN model provides promising results but, the performance ranking of this model is low. Wu et al. [16] framed a major-scale offended Chinese sentiment by draining a huge volume of human-computer conversations. Accurate researches were conducted using CNNs and other traditional machine learning methods.

2.3. Recurrent neural networks (Recurrent NN)

Recurrent NN is a sort of artificial neural network used for successive inputs and the connections are sequential, which are used to process the output based on previous inputs [17]. Recursive neural networks are extremely powerful only because each term is depicted as a vector and an operator (a matrix) that appears to be quite spontaneous [18]. Thereby the term “not” may be considered as a rotational matrix and it plays on next term to change the polarity of that word by turning the good vector to not good. A recurrent neural network is used for word prediction, Music combination, generation of a caption to Image, voice recognition, so on.

Figure 5 depicts the fundamental design of Recurrent Neural Network in which a word vector (*x*_0) is supplied to the function *F*, the output from this function *F* is a standalone output (*h*_0) as well as is fed to the next network in the chain. Now, the sub sequent network takes next word vector (*x*_1) as input along with the previous output *h*_0, produce the next output *h*_1 and so on.

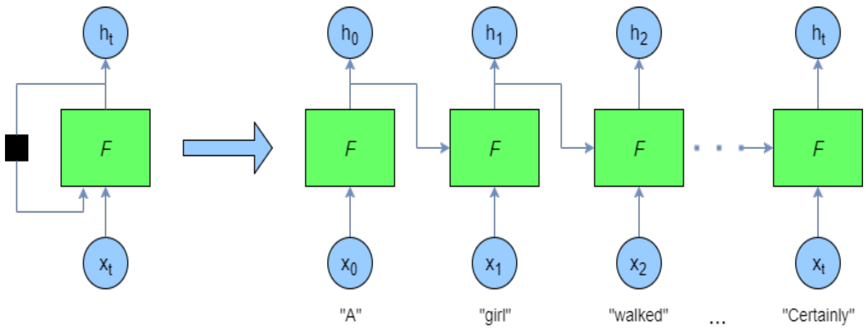

Fig. 5. Fundamental design of recurrent neural network.

Fang et al. [19] developed a model that targets on review embedding with temporal nature toward the commodity. In order to learn a scattered description of commodities and users, a fusion of gated recurrent units with RNN is employed. And these descriptions are fed to machine learning classifier to classify sentiments. The outcome of this model was compared with other existing paradigms such as Recursive NN and analysis of these approaches is given. According to Wei et al., [20], Sentimental Analysis is demonstrated by the strategies for RNN-LSTM. The normal precision of 80% is gained by this model. The precision of the outcomes can be yet improved by having further datasets. Fu et al. [21] have been examined various deep learning recurrent architectures, especially LSTM and Gated Recurrent Units (GRU), in bidirectional and unidirectional forms to discover sentiment polarity of Arabic micro blogs. Rong et al. [22] proposed a selective Recurrent NN model to execute sentiment anatomy by using huge volumes of unlabeled information to instruct a group of word embedding, utilized to set weights. The outcomes of experiments conducted on the datasets show the advancement in efficient polarity detection.

Li et al. [23] evaluated the characteristics of a group of emoticons: “humorous”, stated its human established interpretations after splitting into 3 forms: humorous, positive, negative. 23 emoticons are tabulated which were defined as “humorous” more often than “positive” or “negative”. Hassan et al. [24] presented research on character-level Recurrent NN for Sentiment Analysis in Bangla by relating it with a deep learning model and produced a pleasant result. This research depicts that character-level Recurrent NN is a significant paradigm to pull out the sentiment from Bangla. Baktha and Tripathy [25] analysed standard RNN paradigms on 3 SA datasets. Gated Recurrent Units are referred to as the right selection for accuracy. A deep RNN can be used if the size of the dataset is vast and has prolonged reviews.

2.4. Recursive neural network (Recursive NN)

Recursive NN, a sort of deep neural system made by utilizing a similar arrangement of loads recursively over-organized info. A recursive neural system is a various levelled system where there is extremely no time perspective to the information arrangement; however, the information must be prepared progressively in a tree-style, Irsoy and Cardie [26].

Pennington et al. [27], proposed a model consisting of RNTN (Recursive Neural Tensor Network) and Sentiment Treebank to precisely explain the structural possessions at different degrees of expressions, i.e., positive and negative phrases. After comparing with the current paradigms, it was found that the paradigm cannot determine the signification of lengthy expressions. The RNTN achieved 80.7% accuracy in predicting sentiments. Li et al. [28] proposed a summed up and scaled system to perceive top checking/malware dealers dependent on deep learning for conclusion examination and utilized in string categorization and snowball inspecting to decide the nature of vender's administration/item by dissecting the client criticism. The model has been assessed on the Russian checking gathering and the information identified with the discussions is gathered utilizing a web crawler. Results show that the systems achieve unrivalled results than the shallow classifier's and it was built up that the checking vender's having fewer evaluations than ill-intentioned merchants.

3. Experimental Results

To assess the nature of the methodology, we use experimental results, and the assessment may be in different ways such as objective of the model, experimental goal or sometimes depends on the users' requirement. The experimental results are done on 16-core vCPU's with NVidia Tesla K40 GPU environment.

Performance metrics

To assess the accuracy of the model, we use performance metrics. Some of the performance metrics used to evaluate the deep learning approaches are Computational Time, Training accuracy, Testing Accuracy and validation accuracy.

$$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ Examples} \tag{1}$$

(or)

$$Accuracy = \frac{Number\ of\ True\ Preictions}{Total\ Number\ of\ Predictions\ made} \tag{2}$$

A. Computational time

It can be defined as the running time required for performing a computational process. The portrayal of a calculation as a succession of standard applications, the calculated time is relative to the number of guideline applications executed.

B. Training accuracy

Training accuracy is usually the resultant accuracy when the model is applied to the training data. It tells about how much the model learns to map the input and output to train the model.

$$Training\ ccuracy = \frac{100 * (correctly\ Trained\ )}{Total\ Trained} \tag{3}$$

C. Testing accuracy

Testing accuracy is the accuracy of the testing data. Training data is the data given to the network, from which the network builds the model. The test data is used to check the accuracy for the model built using train data.

F1 Score is used to measure a test's accuracy

F1 Score is the Harmonic Mean between precision and recall. The range for F1 Score is [0, 1]. It tells you how precise your classifier is (how many instances it classifies correctly), as well as how robust it is (it does not miss a significant number of instances).

$$\boldsymbol{F1\ Score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)}} \quad \textbf{(4)}$$

$$\boldsymbol{Precision = \frac{(True\ positives)}{(True\ positives + False\ positives)}} \quad \textbf{(5)}$$

$$\boldsymbol{Recall = \frac{(True\ positives)}{(True\ positives + False\ negatives)}} \quad \textbf{(6)}$$

D. Validation accuracy

Validation accuracy is used to evaluate the performance of the model by taking a small decent sample from test data. It used to tune the hyper-parameters (i.e. the architecture) of a classifier, for example to choose the number of hidden units in neural networks.

Cross-validation can be used to tune the parameters as well as to estimate the test error when enough data set is not available as a validation set.

If the difference between training accuracy and validation accuracy is low, then the model is over-fitted a little; else the model is strongly over-fitted.

4. Discussion

Considering the three data sets and assessing the performance of CNN, Recurrent NN & Recursive NN algorithms –Movie Tweeting, Trending YouTube Video Statistics and Twitter Sentiment Analysis from the Source https://www.kaggle.com/datasets where these data sets were pre-processed already. The details of the datasets like classes, no of instances, attributes, etc. are shown in Table 1.

Table 1. Datasets used in this experiment.

Dataset	Dataset size	Number of attributes	Number of instances	Classes	Training/ Validation Samples
Movie Tweetings	19KB	29	1385	13	15KB/4KB
Trending YouTube Video Statistics	197MB	20531	801	212	152MB/45MB
Twitter Sentiment Analysis	47KB	25	400	32	38KB/9KB

4.1. The computational time for training

The computational time required for training different deep learning models namely Convolutional NN, Recurrent NN and Recursive NN by varying data set size from 10MB to 200MB as shown in Fig. 6.

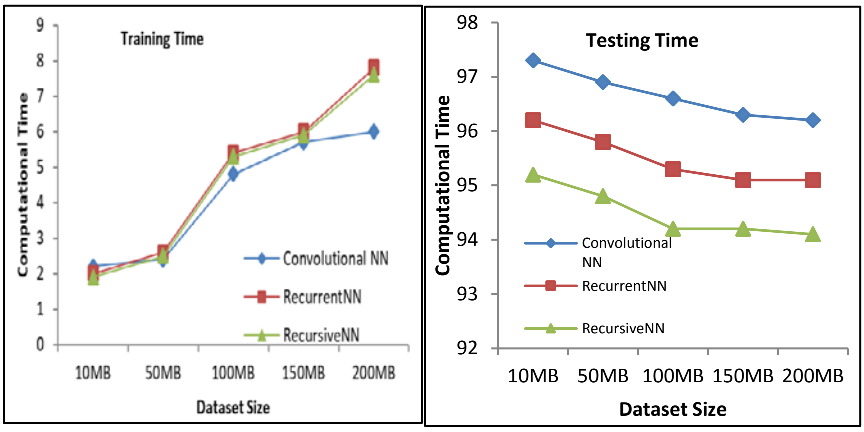

Fig. 6. Computational time required for training and testing of CNN, RNN, Recursive NN.

Training of CNN takes less computational time when compared to Recurrent NN and Recursive NN for small datasets. CNN takes more computational time when compared to Recurrent NN and Recursive NN because the testing computational time of CNN is directly proportional to data set size, therefore the computational testing time increases as the data set size increases.

4.2. The Computational time for testing

The Computational time for Testing of Convolutional Neural networks (CNN) takes more time when compared to Recurrent NN and Recursive NN because the testing computational time of CNN is directly proportional to data set size, therefore the computational testing time increases as the data set size increases as shown in Fig. 7.

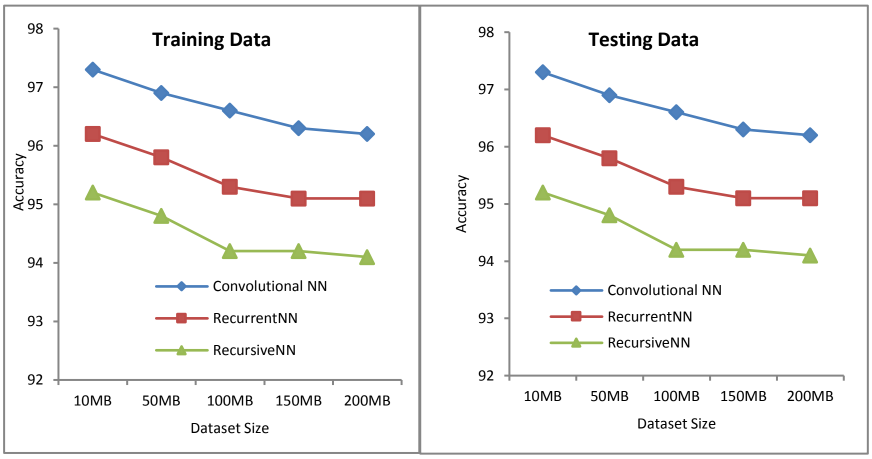

Fig. 7. Overall runtime to find training accuracy and testing accuracy.

4.3. Overall computational time

The overall computational time for the three models namely CNN, Recurrent NN and Recursive NN. The overall computational time is high for CNN because Convolutional Neural networks (CNN) work better with small data points and Recurrent NN and Recursive NN has shorter memory problem.

4.4. Training accuracy

The accuracy of training data set is compared among the three deep learning models CNN, Recurrent NN and Recursive NN respectively. The training accuracy is high for CNN when compared to the other two models.

4.5. Testing accuracy

The testing accuracy is high for CNN when compared to the other two models. Convolutional Neural networks (CNN) works better with large datasets and Recurrent NN and Recursive NN has shorter memory problem while processing the input sequences.

Considering the three data sets and assessing the performance of CNN, Recurrent NN & Recursive NN algorithms with Validation data set to estimate the exact performance of the model or classifier, if our model has a loss of ~0.22 on the training set and <=~0.22 on the validation set. Usually, a loss function is used to optimize any learning algorithm for its better performance i.e. the expected model will perform with good accuracy on new dataset. The training loss and Validation loss for CNN is less when compared with remaining two algorithms, when the dataset is small as shown in Table 2 and Fig. 8.

Table 2. Datasets with training and validation losses.

Data set	Method	Time/epoch	Training loss (10^-2)	Validation loss (10^-2)
Data set1	CNN	26 sec	0.22	0.23
	RNN	84 sec	0.23	0.21
	Recursive	104 sec	0.23	0.24
Data set2	CNN	167 sec	0.3121	0.312
	RNN	298 sec	0.3541	0.354
	Recursive	197 sec	0.322	0.321
Data set3	CNN	39 sec	0.262	0.261
	RNN	124 sec	0.293	0.292
	Recursive	136 sec	0.268	0.267

Validation accuracy is different from training accuracy. If the validation accuracy is greater than training accuracy then the model is said to be under-fitted, to avoid this we need to increase the number of layers in the model. Validation set actually can be considered as a decent sample of test set, because it is used to build your model, neural networks or others. It is usually used for parameter selection and to avoid over-fitting. Suppose our model has an accuracy of ~95.8% on the training set and ~93.1% on the validation set. This means that expected performance of the model with ~93.1% accuracy on new dataset.

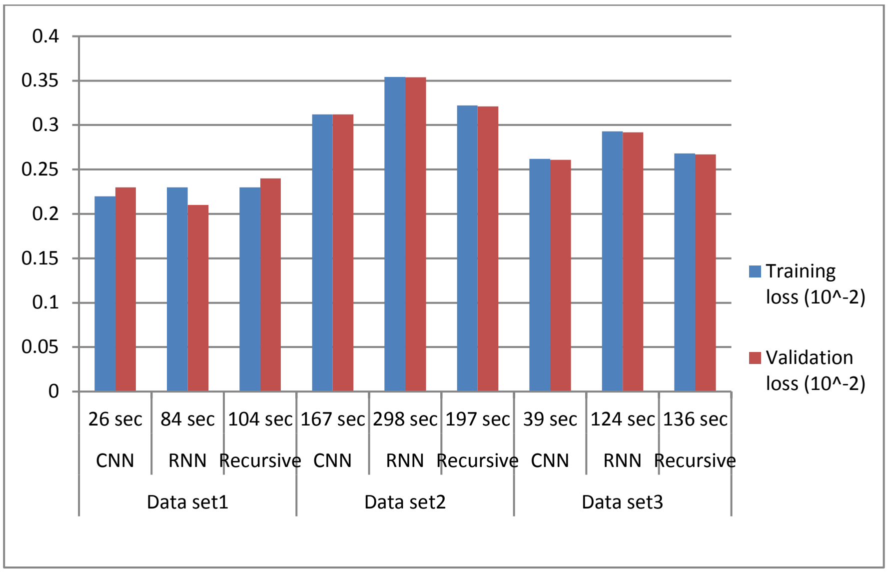

Fig. 8. Details of training and validation loss.

When the dataset is small, the CNN performs well, for large datasets the Recurrent NN & Recursive NN performs better than CNN shown in Table 3.

Table 3. Datasets with training and validation accuracy.

Data set	Method	Time/epoch	Training accuracy	Validation Accuracy
Data set1	CNN	26 sec	95.8	93.1
	RNN	84 sec	94.2	93.9
	Recursive	104 sec	92.8	92.6
Data set2	CNN	167 sec	89.23	88.1
	RNN	298 sec	86.6	85.5
	Recursive	197 sec	88.98	87.3
Data set3	CNN	39 sec	92.6	90.2
	RNN	124 sec	91.2	89.9
	Recursive	136 sec	91.1	90.1

5. Conclusion

Sentiment analysis can be determined as a process for identifying the emotions with the help of a series of words which are used in online sites. It plays a crucial role in this digital world. To attain sentiment analysis with unstructured data available as input, traditional mechanisms are failed due to the nature of the data available. For that, in this paper, we made a comprehensive analysis of deep learning-based sentiment analysis techniques. This paper presented an empirical survey on the methods learning of deep such as CNN, Recurrent NN and Recursive NN achieved its A1 and A2 satisfied with a proper explanation about all these neural networks. R1 is achieved with justified Comparative performance of all these neural networks, by taking the data set size varying from 10MB to 200MB and by considering the factors like computational time and training, testing and validation accuracy. In the discussion, exhibits the better Performance results and proves that CNN is better than Recurrent NN and Recursive NN for sentiment analysis because of CNN architectural flexibility and also proved our hypothesis H1. As future work, a flexible model for analysing sentiments based on Convolutional neural networks will be proposed for images and videos as input to the model. For analysing text and speech as input, we can go for Recurrent NN and Recursive NN.

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