Deep Learning Techniques: A Review

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Abstract

Deep Learning models are effective due to their automatic learning capability. This review paper highlights latest studies regarding the implementation of deep learning models such as deep neural networks, convolutional neural networks and many more for solving different problems of sentiment analysis such as sentiment classification, cross lingual problems, textual and visual analysis and product review analysis.

Keywords—*Deep Learning, sentiment analysis, recurrent neural network, deep neural network, convolutional neural network, recursive neural network, deep belief network*

I. INTRODUCTION

A. Deep Learning

Deep learning is an artificial intelligence function that imitates the workings of the human brain in processing data and creating patterns for use in decision making. Deep learning is a subset of machine learning in artificial intelligence that has networks capable of learning unsupervised from data that is unstructured.

Deep learning includes many networks such as CNN (Convolutional Neural Network), RNN (Recurrent Neural Network), Recursive Neural Network, DBN (Deep Belief Network) and many more. Neural networks are very beneficial in text generation, vector representation, word representation estimation, sentence classification, sentence modelling and future presentation.

B. Sentiment Analysis

Sentiment analysis also known as Opinion Mining is a field within Natural Language Processing (NLP) that builds systems that try to identify and extract opinions within text. Usually, besides identifying the opinion, these systems extract attributes of the expression such as:

- Polarity: if the speaker expresses a positive or negative opinion,
- Subject: the thing that is being talked about,
- Opinion holder: the person, or entity that expresses the opinion.

With the help of sentiment analysis systems, this unstructured information could be automatically transformed into structured data of public opinions about products, service, brands, politics, or any topic that people can express opinions about. This data can be very useful for commercial applications like marketing analysis, public relations, product reviews, net promoter scoring, product feedback, and customer service.

II. LITERATURE REVIEW

For the accurate classification of sentiments, many researchers have made efforts to combine deep learning and machine learning concepts in the recent years. This section briefly describes the numerous studies, related to sentiment analysis of web contents about users' opinions, emotions, reviews toward different matters and products using deep learning techniques.

A. ***Convolutional Neural Network (CNN)***

This study [4] has proposed a novel convolution neural network framework for visual content. CNN has been implemented using Caffe and Python on a Linux machine. Transfer learning approach and hyper-parameter has been used in biases and weights are utilized from pre-trained GoogLeNet.

The authors [5] have proposed the system of deep learning for sentiment analysis of twitter. The main focus of this work was to initialize the weight of parameters of convolutional neural network and it is critical to train the model accurately while avoiding the requirement the requirement of adding new feature.

A detailed research by [6] has presented an overview of sentiment analysis related to Micro-blog. The purpose of this effort was to get the opinions and attitudes of users about hot events by using CNN. The use of CNN overcomes the problem of explicit feature extraction and learns implicitly through training data.

Research by [7] was motivated through the need of controlling of comprehensive social multimedia content and employ both textual and visual SA techniques for combined textual-visual sentiment analysis. A CNN and a paragraph vector model were used for both the image and textual SA accordingly.

In study by [2] the researcher has represented a seven layer framework to analyse the sentiments of sentences. This framework depends on CNN and Word2vec for SA and to calculate vector representation, respectively.

B. *Recursive Neural Network (RNN)*

The proposed work [8] builds a Treebank for chines sentiments of social data to overcome the deficiency of labelled and large corpus in exiting models. To predict the labels at sentence level i.e. positive or negative, the RNDM was proposed and achieved high performance than SVM, Nave Bayes and Maximum Entropy.

In this study [9], a model comprising RNTN and sentiment Treebank has been proposed to correctly clarify the compositional efforts at different levels of phrases.

This study [10] has contributed a generalized and scaled framework to recognize top carding sellers. The model is based on deep learning for sentiment analysis and used in thread classification and snowball sampling to assess the quality of seller's product by analysing the customer feedback.

C. *Deep Neural Network (DNN)*

In this study [11] author has proposed a model for sentiment analysis considering both visual and textual contents of social networks. This new scheme used deep neural network model such as Denoising auto encoders and skip gram. The base of the scheme was CBOW model.

In this study [12] deep neural network architecture has been proposed to evaluate the similarity of documents. The architecture was trained by using several market news to produce vectors foe articles. The T&C news have been used as dataset. The cosine similarity was calculated among labelled articles and the polarity of documents was considered but contents were not considered.

D. *Recurrent Neural Network (Recurrent NN)*

In this study [13] the HBRNN (hierarchical bidirectional recurrent neural network) has been developed to extract the reviews of customers about different hotels in a complete and concise manner. HBRNN has used the terminology of RNN and the prediction process was done at review level by HBRNN.

This contribution [14] has been done to overcome the issue of dataset of Bangla as it is standard and large for SA tasks. The issue has been resolved by providing a significant dataset for sentiment analysis of 10,000 BRBT. The Deep Recurrent model especially LSTM was used to test the dataset by using two loss functions.

This author [15] proposed a sequence model to focus on the embedding of reviews having temporal nature toward products as these reviews had less focus in existing studies.

To overcome the deficiency of labelled and large corpus in exiting models. To predict the labels at sentence level i.e. positive or negative Deep Belief Networks (DBN)

In this paper [17] a new deep neural network structure has been presented termed as WSDNNs (Weakly Shared Deep Neural Networks). The purpose of WSDNNs is to facilitate two languages to share sentiment labels.

DBN [16] includes several hidden layers, composed by RBM (restricted Boltzmann machines). DBN has been proved efficient for feature representation. It utilizes the unlabelled data and fulfils the deficiencies of labelled analysis issues.

Another study by [3] has used DBN with word vector for the political detection in Korean articles. The proposed model has used SVM for bias, python web crawler to gather news articles, KKMA for morpheme analysis, word2Vec and scikit-learn package.

E. *Hybrid Neural Networks*

This study [1] has proposed two deep learning techniques for the sentiment classification of Thai Twitter data, i.e. CNN and LSTM.

In this research study [18] a hybrid model has proposed which consists of Probabilistic Neural Network and a two layered Restricted Boltzmann. The purpose of proposing this hybrid deep learning model is to attain better accuracy of sentiment classification.

F. *Other Neural Networks*

In this study [19] to overcome the complexity in word-level models the character-level model has been proposed. The motivation of proposed model CDBLSTM is an existing model that is DBLSTM neural networks [20]. The focus of this work is only on textual content and on the polarity analysis of tweets in which a tweet is classified into two classes, i.e. positive and negative.

This contribution [21] overcomes the problem that occurs in effectively analysing the emotions of customers toward companies in blog sphere. A neural network (NN) based technique is proposed which subordinate the advantages of Semantic orientation index and machine learning methods for the classification of sentiments effectively and quickly.

This contribution [22] proposed a data driven supervised
approach for the purpose of feature reduction and development of lexicon specific to twitter sentiment analysis about brand.

Researcher Name And Year	Model Used	Purpose	Data Set	Results
J.Islamm and Y. Zhang 2016 [25]	Convolutional Neural Network (CNN)	Visual SA	1269 images from twitter	GoogleNet gave almost 9% performance progress than AlexNet.
A. Severyn and A. Moschitti, 2015 [26]	Convolutional Neural Network (CNN)	Phrase level and message level task SA	Semeval-2015	Compared with official system ranked 1st in terms of phrase level subtask and ranked 2nd in terms of message level.
L. Yanmei and C. Yuda. 2015 [27]	Convolutional Neural Network (CNN)	Micro-Blog SA	1000 micro-blog comments	Proposed model can effectively improve the accuracy of emotional orientation, validation.
Q. You, J. Luo, H. Jin, and J. Yang, 2015 [28]	Convolutional Neural Network (CNN)	Textual-visual SA	Getty images, 101 keywords	Joint visual and textual model outperforms the early single fusion.
X. Ouyang, P. Zhou, C. H. Li, and L. Liu, 2015 [15]	Convolutional Neural Network (CNN)	Sentiments of sentences	Rottentomatoes.com (contains movie review excerpts)	The proposed model outperformed the previous models with the 45.5% accuracy.
C. Li, B. Xu, G. Wu, S. He, G. Tian, and H. Hao, 2014 [29]	Recursive Neural Deep Model (RNDM)	Chines sentiments analysis of social data	2270 movie reviews from websites	Performs higher (90.8%) than baselines with a great margin.
R. Socher, A. Perelygin, and J. Wu, 2013 [30]	Recursive Neural Tensor Network (RNTN)	Semantic Compositionality	11,855 single sentences from moview review (Pang and Lee 2005)	The RNTN achieved 80.7% accuracy in sentiment prediction, an improvement of 9.7% over baselines (bag of features).
W. Li and H. Chen, 2014 [31]	Recursive Neural Network (RNN)	Identifying Top sellers In underground Economy	Russian Carding Forum	Results have been indicated that deep learning techniques accomplish superior outcomes then shallow classifiers. Carding sellers have fewer ratings than malware sellers.
C. Baecchi, T. Uricchio, M. Bertini, and A. Del Bimbo, 2016 [32]	Deep neural networks (CBOW-DA-LR)	Visual and Textual SA	4 datasets: Sanders Corpus, Sentiment140, SemEval-2013 and SentiBank Twitter Dataset	CBOW-DA-LR model obtained superior classification accuracy than previous models.
H. Yanagimoto, M. Shimada, and A. Yoshimura, 2013 [33]	Deep Neural Network (DNN)	Document Similarity Estimation	T&C News	The proposed method accomplished superior performance in terms of similarity estimation of articles according to polarity.
R. Silhavy, R. Senkerik, Z. K. Oplatkova, P. Silhavy, and Z. Prokopova, 2016 [34]	Hierarchical bidirectional Recurrent Neural Network (HBRNN)	Sentiment analysis of customer reviews	150,175 labelled Reviews from 1500 hotels (DBS text mining Challenge 2015)	The experimental results explored that HBRNN outperformed all other methods.
A. Hassan, M. R. Amin, A. Kalam, A. Azad, and N. Mohammed, [35]	Deep Recurrent model especially LSTM (Long Short Term Memory)	Sentiment Analysis on Bangla and Romanized Bangla Text (BRBT)	9337 post samples from different social sources	Ambiguous Removed with 78%accuracy. Ambiguous converted to 2 scored highest with 55% accuracy.

T. Chen, R. Xu, Y. He, Y. Xia, and X. Wang, 2016 [36]	Recurrent Neural Network (RNN-GRU)	Learning User and Product Distributed Representations	Three datasets collected from Yelp and IMDB	Results have been indicated that proposed model outperformed many baselines including recursive neural networks, user product neural network, word2vec, paragraph vector and algorithm JMARS
G. Zhou, Z. Zeng, J. X. Huang, and T. He, 2016 [38]	WSDNNs (Weakly Shared Deep Neural Networks)	Cross-Lingual Sentiment Classification	Four languages reviews from amazon, each language consists of 1000 negative and 1000 positive reviews	Proposed approach is more effective and powerful than the previous studies by applying experiments on 18 tasks of cross lingual sentiment classification.
T. Mikolov, K. Chen, G. Corrado, and J. Dean, 2013 [17]	Deep Belief Networks Along with word vector	Political Detection in Korean articles	50,000 political articles	Results showed 81.8% accuracy by correctly predicting labels.
P. Ruangkanokmas, T. Achalakul, and K. Akkarajitsakul, 2016 [37]	Deep Belief Network with Feature Selection (DBNFS)	Feature Selection	Five sentiment classification datasets (1 is movie reviews and other four are multidomain). Total 2,000 labeled reviews (1,000 negatives and 1,000 positives).	The accuracy results are compared with previous works and proved better DBNFS than DBN.
P. Vateekul and T. Koomsubha , 2016 [8]	Convolutional Neural Network (DCNN) and Short Term Memory(LSTM).	Sentiment Analysis on Thai Twitter Data	3,813,173 tweets (33,349 negative tweets and 140,414 positive tweets)	Higher in accuracy than SVM and Nave Bayes lesser than Maximum Entropy Higher accuracies in original sentences than shuffled sentences
R. Ghosh, K. Ravi, and V. Ravi, 2016 [39]	Probabilistic Neural Network (PNN) and a two layered Restricted Boltzmann (RBM)	Better accuracy of sentiment classification	Pang and Lee and Blitzer, et al. (1000 negative and 1000 positive reviews on each of DVDs, Books (BOO), Kitchen appliances (KIT) and Electronics (ELE).	The proposed model attains accuracies in following manner: MOV = 93.3%, BOO = 92.7%, DVD = 93.1%, ELE = 93.2%, KIT = 94.9%
R. Goebel and W. Wahlster, 2011 [40]	Deep Bi-directional Long Short-Term Memory Neural Networks (DBLSTM)	Sentiment Analysis of Social Data	SemEval 2016 and the second one is provided by Go dataset (1.6 million tweets)	85.86% accuracy was achieved on STS (Stanford Twitter Sentiment) corpus 84.82% on SemEval-2016.
K. Ravi and V. Ravi, 2016 [41]	Radial Basis Function Neural Network (RBFNN)	Sentiment classification on Hinglish text	300 news articles from viz. news and facebook.	The proposed approach performed better sensitivity than specificity in terms of news dataset. The proposed approach performed better specificity than sensitivity in terms of fb dataset.

L.-S. Chen, C.-H. Liu, and H.-J. Chiu, 2011 [42]	Back Propagation Neural Network (BPN)	Sentiment classification in the blogosphere	LiveJournal and Review Center have been used to collect reviews	Results concluded that proposed method enhance performance of classification and save training time as compared to traditional ML and IR.
M. Ghiassi, J. Skinner, and D. Zimbra, 2013 [43]	Dynamic Artificial Neural Network (DANN)	Twitter brand Sentiment analysis (for justin bieber brand)	Total 10,345,184 tweets related to justin bieber brand	Results concluded that: More than 80% tweets dont have sentiment. Reduced feature set with characterize 97.3% of all messages in the 10,345,184 Justin Bieber Twitter corpus. Only six expressions were found related to Justin Bieber brand out of 181 and other were found twitter specific. Facilitates the Justin Bieber brand to identify the issues and views about the brand.

CONCLUSION

This review has described ample of studies related to sentiment analysis by using deep learning models as summarized in Table I. After analysing all these studies, it is established that by using deep learning methods, sentiment analysis can be accomplished in more efficient and accurate way.

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