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Procedia Computer Science 218 (2023) 220–226

Procedia Computer Science

www.elsevier.com/locate/procedia

International Conference on Machine Learning and Data Engineering

Text Sentiment Analysis based on Multichannel Convolutional Neural Networks and Syntactic Structure

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Abstract

Over the last few years, the recognition of social media has grown exponentially, and emotional evaluation in critiques, feedback and evaluations from social media has become extra effective inside the studies field. excessive satisfactory, emotional analysis expresses ideas about real-time gadgets, merchandise, films and tweet evaluations. With the sheer quantity of person-generated text on social media, Emotional evaluation (SA) has become an fundamental a part of NLP with many programs, including statistics retention and retrieval techniques, net design, and plenty extra. Convolutional Neural community (CNN) and Recurrent Neural community (RNN) were widely used in the area of textual emotional analysis and feature yielded wonderful results. during the last few years, the recognition of social media has grown exponentially, emotional evaluation in critiques, comments and opinions from social media has end up more effective within the studies subject. excessive high-quality, emotional analysis expresses ideas about real-time items, products, movies and tweet reviews. Bidirectional Recurrent Neural community can triumph over CNN's failure to extract semantic data for lengthy textual content, however it can't extract the area features of the textual content as CNN can do it. The model can pay attention to key phrases inside the mood the separation of polarity in a sentence by using way of attention and combined with the benefits of CNN extracting nearby textual content capabilities and CNN redirected to extract long-term semantic information textual content, which develops the potential to extract a textual content element using a model. The experimental outcomes on the IMDB film evaluation dataset which show that the proposed version can extract rich textual content features can attain higher results with the schooling accuracy appears to be 87% and schooling loss is 0.2852 while the validation accuracy is 86% and validation loss is 0.3263. The check accuracy effects as 86.132% and check loss is 0.330.

Keywords: Deep Learning, Python, Recurrent Neural Network, sentiment analysis

1. Introduction

This study reveals the novel-based attention of CNN [2,3] and the Bi-LSTM network to find a place of attention that combines key words, feelings that face problems over and over again. CNN is used to read the context of a high-level feature that comes from input representation. at the same time, the focus method is used in the CNN release sections to get proper attention in the various texts. Finally, Bi-LSTM is employed to extract data from CNN-developed sensory

10.1016/j.procs.2023.01.004

analysis layers. To prevail, we employ overuse, as well as Gaussian sound and Gaussian Dropout in the input layer. We chose four Twitter data points because it is a communication platform that thrives on the usage of short forms that are difficult to master due to numerous spelling problems, including polysemy and informal language. Because people on social media frequently use improper spelling, a single misspelling can completely affect the meaning of a text. Preprocessor functions that eliminate noise, lemmatize, and measure special characters have also been employed. For the suggested model, we tested a variety of benchmark performance data sets. People today use social media [4,5,7] to communicate their views and opinions in order to exchange ideas, such as Twitter [1], Facebook, LinkedIn, and WebChat. Researchers were able to investigate popular opinion and ideas owing to the data obtained from these media outlets. Emotional Analysis (SA) has become a fundamental aspect of NLP [13] with various applications, including data preservation and retrieval methods, web editing, and much more, due to the vast amount of user-generated content on social media. Text processing is required to keep in mind the ultimate goal of analyzing and extracting data quickly. Despite the fact that the amount of data in social media graphics is rapidly increasing, standard algorithms frequently fail to extract emotion from such vast amounts of data. Deep learning (DL) methods are now being used by researchers [8,9,10] based on a distributed presentation to address data specification between feature training sets, feature engineering, and more. tackling problems with traditional strategies. Studies show that CNN and RNN work well on DL in a few cases, especially in sensory detection. CNN convolutional works on NLP to create a map and integration feature that is used in more than consecutive sizes to achieve a fixed length effect. This process enables local features for taking photos but you lose content information. However, it is also deceptive in CNN networks to remove remote features, and the compilation layer cannot scan local data.

The paper is organized into five sections. In section 2 related work on text classification models are described. Section 3 presents the model selection and implementation details of the research work. Section 4 shows the results analysis of the developed models. Finally, the research work is concluded in section 5.

2. Related Work

This section discusses the models used for classifying the text data. Further subsections describes the model details.

2.1 Sequential Model

The convolutional neural network is a special type of neural feed network shown in Fig.1. In a normal neural network, neurons of all layers are on one side. The convolutional neural network [6] is designed to process multidimensional data. CNN has two key concepts - location communication and parameter sharing. These concepts reduce the number of parameters to be trained. • Sequential layer • Hub background • Dense layer Sequential model is a series of layers. Limited because it does not allow us to build layers that share layers or have multiple inputs or outputs. Sequential models can be generated by creating a layer of layers and passing through the builders or we can add layers using. add ().

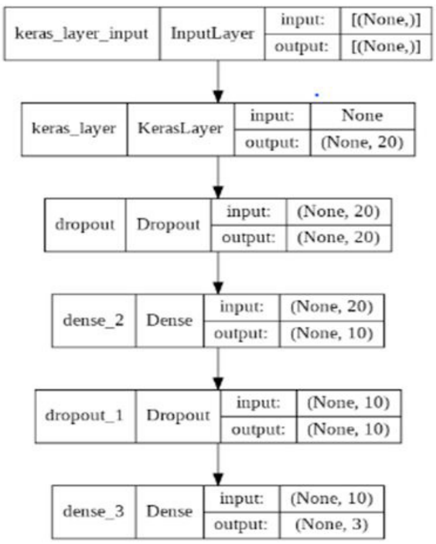

Fig.1. Architecture of Sequential model

2.2 Gated Recurrent Unit (GRU)

The GRU combines a reset gate and a update gateway to a duplicate neural network with a gate which is shown in Fig.2. This model solves the problem of extinction gradient facing common neural networks (RNN). When resetting near 0, ignore the previously hidden status (allows the model to discard non-essential information in the future). If the gamma (review gate) is close to 1, then we can copy the information to that unit in many steps. Gamma Controls how much of the past should be important now.

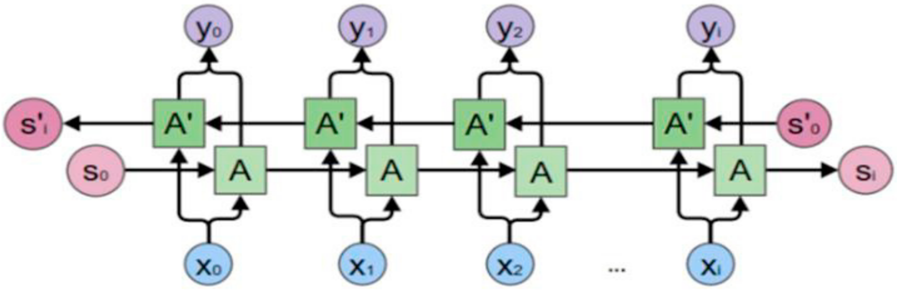

Fig.2. Architecture of Bidirectional GRU

3. Methodology

Pre-processing is a crucial stage in making a text easier to understand by removing irrational phrases, noise, and excessive repetition in order to enhance the efficiency of a deeper model. The vocabulary used on social media, on the other hand, is new and disorganized, and the sound must be loud and clear before being fed into the network. In order to handle all audio and make text ready for training, we apply a range of processing techniques such as lemmatization, eliminating non-Unicode, non-English characters, and User handles instead of URLs. LSTMs are very similar to GRUs, which are also intended to resolve extinction gradient problems. Here are 2 more gates introduced (Forget and Remove) in addition Update GRU gate. Forget the gateway controls what is stored compared to the forgotten, from the previous cell state. According to ordinary people, it will determine how much information from the previous government should be kept and forgotten to stay.

According to the names of ordinary people, it will determine how much information from the previous state should be stored and forget the reas is shown in Fig.3.

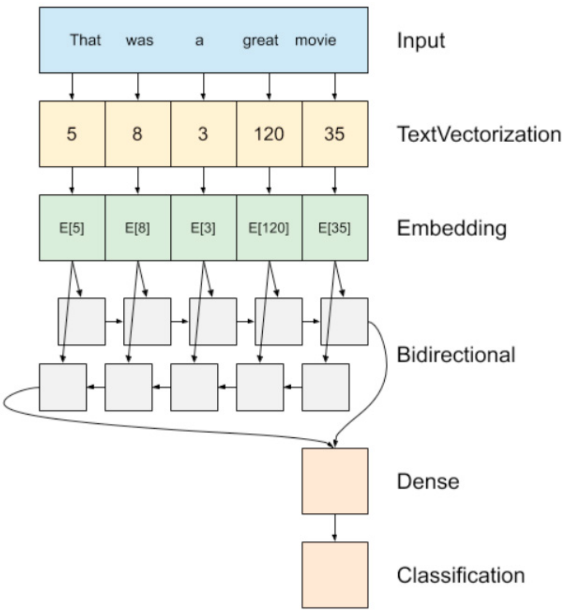

Fig.3. Architecture of Bidirectional Multichannel LSTM model

The Fig.4. shows the algorithmic flow of the system. The dataset is collected from IMDB and preprocessed using various techniques like emoji removal, punctuation removal, stop words and semantic checks of each word [11]. Further, the RNN model is trained using this dataset and cross validated to get the accuracy of the model. Then testing is done and model performance is carried out to check the performance of the model.

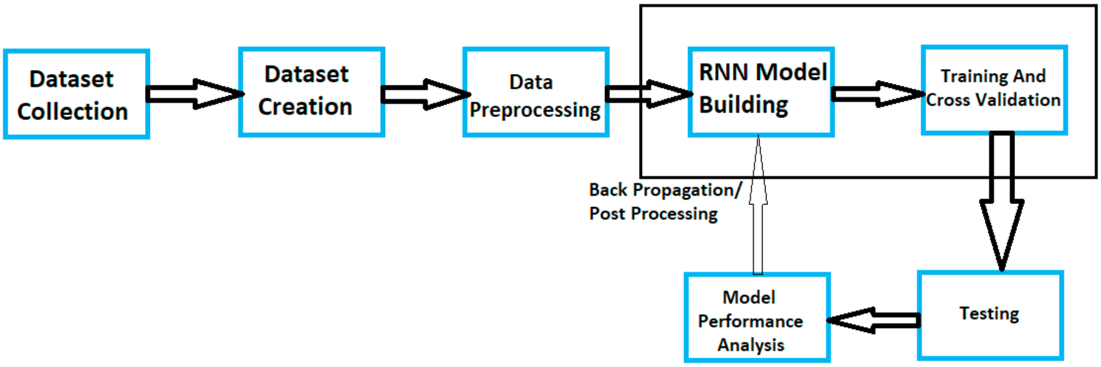

Fig.4. Algorithmic flow of the system

4. Results Analysis

4.1 Graphical representation of epoch vs accuracy

The Fig.5. shows the bidirectional multichannel model's epoch vs accuracy graph. Here, it can be observed that the model tends to fit properly and accuracy of training as well as validation has improved a lot by increasing the line graph slope gradually with an increase in the epoch.

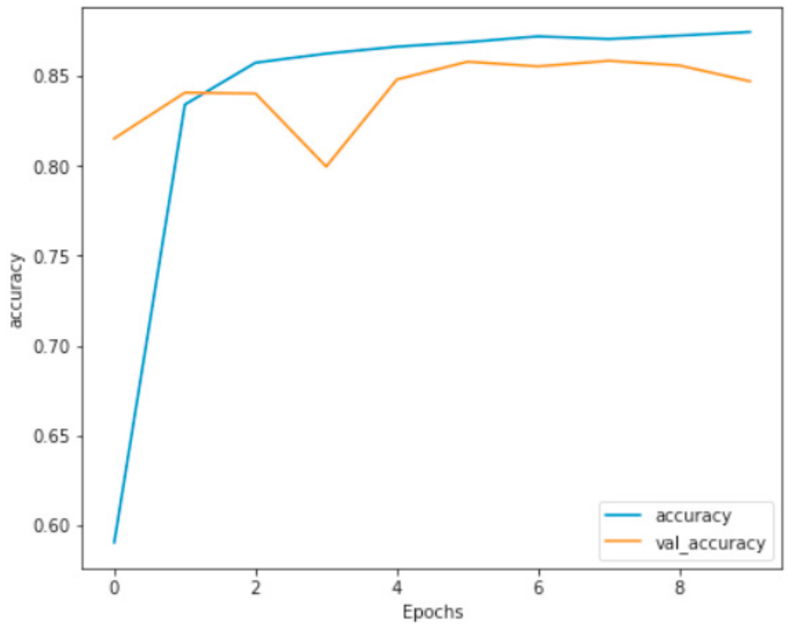

Fig.5. Bidirectional Multichannel LSTM Models epoch vs accuracy graph

4.2 Graphical representation of epoch vs loss

The Fig.6. shows bidirectional multichannel model's epoch vs loss graph. Here, it can be observed that model tends to fit properly and loss of training as well as validation has improved a lot by decreasing the line graph slope gradually with increase in epoch. The line graphs of both training and validation has almost touched the x-axis.

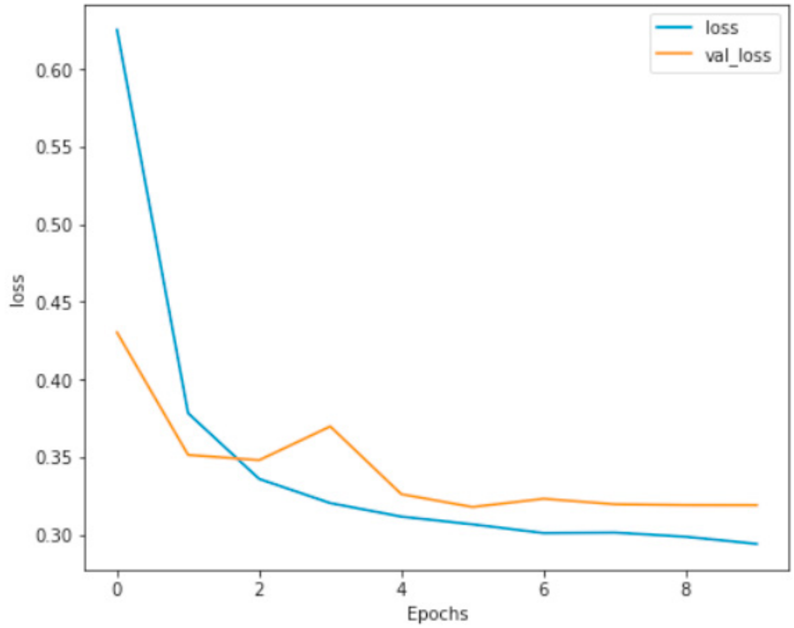

Fig.6. Bidirectional Multichannel LSTM Models epoch vs loss graph

4.3 Comparative Result of models

Table 1. shows the comparative result with respect to the accuracy of each model [12]. The bar plot of accuracy with respect to all models gives clear representation. The Fig.7. shows it through which we can conclude that Multichannel Bidirectional Hybrid LSTM performed better compared to other models.

Table 1. Comparative Relust analysis of different survey models

Models	**SimpleRNN**	**GRU**	**LSTM**	**Multichannel Hybrid LSTM**
Accuracy	87.62	87.41	87.08	87.75

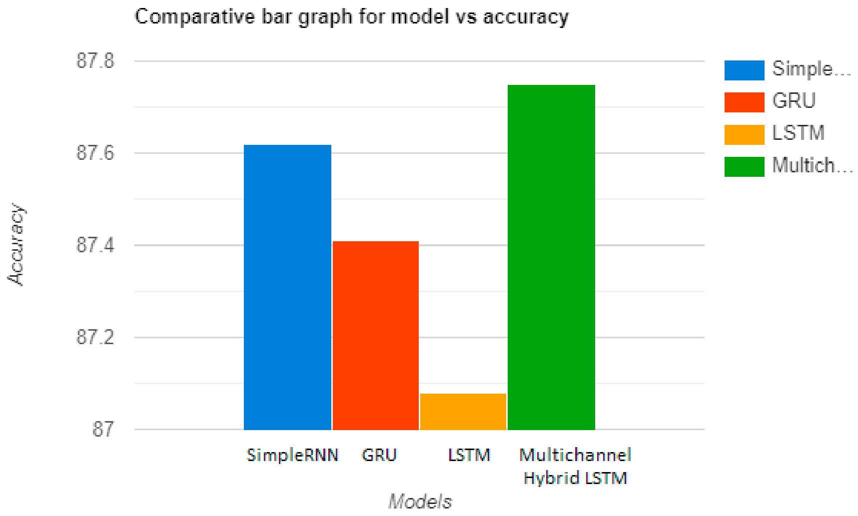

Fig.7. Result analysis of various models with their accuracy

5. Conclusions

This research examined the multi-channel CNN's neural network model as well as the bidirectional LSTM model. The model does not use CNN only to extract local features between texts but also uses bi-directional LSTM to capture global semantic information for sentence context, and the addition of the attention span may be better as words in the sentence can contribute very much to separating emotions. The training accuracy appears to be 87.75 % with a training loss of 0.2852 after 10 epochs, while the validation accuracy appears to be 86.67 % with a validation loss of 0.3263. The test accuracy is 86.132 %, while the test loss is 0.330 %. Several results from tests on two public databases demonstrate the proposed model's full suitability; this hybrid approach of the multiple channels model outperforms CNN and bidirectional GRU in output components, and the proposed model achieves the best differentiation results in the two public databases when compared to other basic models. The proposed model can extract local features via CNN and certain semantic contextual information using multichannel bidirectional LSTM.

References

[1] Z. Jianqiang and G. Xiaolin, "Comparison Research on Text Pre-processing Methods on Twitter Sentiment Analysis," in IEEE Access, vol. 5, pp. 2870-2879, 2017, doi: 10.1109/ACCESS.2017.2672677.

[2] M. Dong, Y. Li, X. Tang, J. Xu, S. Bi and Y. Cai, "Variable Convolution and Pooling Convolutional Neural Network for Text Sentiment Classification," in IEEE Access, vol. 8, pp. 16174-16186, 2020, doi: 10.1109/ACCESS.2020.2966726.

[3] Yoon Kim, Convolutional Neural Networks for Sentence Classification. , Association for Computational Linguistics, 2020

[4] .J. Hutto , A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text, Proceedings of the International AAAI Conference on Web and Social Media , 2020

[5] Lu Shang , Sentiment analysis of film reviews based on CNNBLSTM-Attention, IFIP TC12 ICIS , 2020

[6] Richard Sutcliffe , Improving Arabic Sentiment Analysis Using CNN-Based Architectures and Text Preprocessing., Computational Intelligence and Neuroscience , 2021

[7] Qianzi Shen and Zijian Wang and Yaoru Sun, Sentiment Analysis of Movie Reviews Based on CNN-BLSTM, IFIP TC12 ICIS, 2017

[8] S. Paliwal, S. Kumar Khatri and M. Sharma, "Sentiment Analysis and Prediction Using Neural Networks," 2018 International Conference on Inventive Research in Computing Applications (ICIRCA), 2018, pp. 1035-1042, doi: 10.1109/ICIRCA.2018.8597358.

[9] A. Chachra, P. Mehndiratta and M. Gupta, "Sentiment analysis of text using deep convolution neural networks," 2017 Tenth International Conference on Contemporary Computing (IC3), 2017, pp. 1-6, doi: 10.1109/IC3.2017.8284327.

[10] Yazhi Gao, W. Rong, Y. Shen and Z. Xiong, "Convolutional Neural Network based sentiment analysis using Adaboost combination," 2016 International Joint Conference on Neural Networks (IJCNN), 2016, pp. 1333-1338, doi: 10.1109/IJCNN.2016.7727352.

[11]S. G. Kanakaraddi and S. S. Nandyal, "Survey on Parts of Speech Tagger Techniques," 2018 International Conference on Current Trends towards Converging Technologies (ICCTCT), 2018, pp. 1-6, doi: 10.1109/ICCTCT.2018.8550884.

[12]S. G. Kanakaraddi, A. K. Chikaraddi, K. C. Gull and P. S. Hiremath, "Comparison Study of Sentiment Analysis of Tweets using Various Machine Learning Algorithms," 2020 International Conference on Inventive Computation Technologies (ICICT), 2020, pp. 287-292, doi: 10.1109/ICICT48043.2020.9112546.

[13]S. G. Kanakaraddi and V. Ramaswamy, "Natural language parsing using Fuzzy Simple LR (FSLR) parser," 2014 IEEE International Advance Computing Conference (IACC), 2014, pp. 1337-1341, doi: 10.1109/IAdCC.2014.6779521.

[14]Kanakaraddi, S.G., Chikaraddi, A.K., Aivalli, N., Maniyar, J., Singh, N. (2022). Sentiment Analysis of Covid-19 Tweets Using Machine Learning and Natural Language Processing.Proceedings of Third International Conference on Intelligent Computing, Information and Control Systems. Advances in Intelligent Systems and Computing, vol 1415. Springer, Singapore.

[15] Zhou Gui Zhou, "Research on Sentiment Analysis Model of Short Text Based on Deep Learning", Scientific Programming, vol. 2022, Article ID 2681533, 7 pages, 2022.

]16] Gong Xiaokang, Ying Wenhao, Zhong Shan, Gong Shengrong, Text Sentiment Analysis Based on Transformer and Augmentation, Frontiers in Psychology, 2022