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PERFORMANCE ANALYSIS OF DIFFERENT DEEP LEARNING TECHNIQUES FOR DETECTING FAKE NEWS

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Abstract

Fake news is defined as news items which are not real, genuine and are generated to deceive or mislead users. With the rise in great demand for social networking sites, the distribution of fake news has become a major threat to various sectors. The process of seeking news articles from social networking sites is like a double-edged weapon [1]. On one side it is easy to access news from social networking sites. And on the other hand, the news being obtained on social media is being manipulated for personal interests. So there is a great need to identify fake news and promote the spread of genuine information. In this paper, different deep learning techniques are described and their performance is evaluated in detecting fake news

I. Introduction

The great revolution and rise of information and communication technologies has drastically and exceptionally increased the number of people with access to the Internet, which has dramatically changed the way the information is propagated or discharged. Due to more number of Internet users, the spread of fake news have become one of the greatest threats to society, individuals, organization, and government.

Fake news can be described as misinformation or manipulated news which is spread either on traditional media or social networking sites with the aim to damage any person's agency or organization. In the past, fake

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news is propagated through traditional media like television news, newspapers, etc. [2]. The term “Fake news” on social media gained popularity during the US electoral campaign of 2016.

The recent scenario of the COVID-19 pandemic shows a huge increase in the fake news articles through social media misleading people and getting undue benefits. The adverse effects of this fake news made people believe that COVID only affects old age people, not children and young people. There is much other misinformation’s such as vaccines are developed, masks do not prevent the virus from the spread, and many more.

Technologies such as Deep Learning, Natural Language Processing provide better results in efficiently identifying fake news from real news. In this paper different deep learning techniques are described that can be used for detecting fake news and to evaluate which model performs best in detecting the fake news.

II. Proposed Work

Many machine learning techniques are described for detecting fake news such as Naïve Bayes, Support Vector Machine, Decision Trees, Random forest. The results obtained by these machine learning techniques are not very efficient in detecting fake news as the news in the online social media related to fake news is huge and machine learning techniques cannot efficiently evaluate such a huge amount of data.

Deep learning techniques can outcome the problem obtained due to machine learning techniques that is deep learning techniques that can efficiently process huge volumes of data. In this paper, the different deep learning techniques described are Shallow Convolution Neural Network, Long Short Tem Memory (LSTM), Gated Recurrent Neural Network (GRU), Convolution Neural Network with Long Short Tem Memory (CNN+LSTM), Multi-Channel Convolution Neural Network, Deep convolution Neural Network.

Deep learning models to be implemented requires preprocessing of the dataset. The steps involved in preprocessing of the two datasets are Word Tokenization, Text Lemmatization, and Stemming. These are natural language processing techniques used for text preprocessing as dataset mainly contains text information regarding fake news. Word embedding is a way to represent document vocabulary. It is capable of capturing the context of a word and detecting the semantic and syntactic similarity, relation with other words, etc. In this paper, the word embedding technique used is the GLoVE word embedding. A GLoVe is an open-source tool used for word embedding. It takes word –word co-occurrence statistics from a corpus and reduces a sparse matrix into a dense one by matrix factorization.

The two datasets used are getting real about fake news, COVID-19 fake news. The data in the dataset is divided into 80% training and 20% testing set. The performance is measured by accuracy.

1. Shallow Convolution Neural Network

Shallow Convolution Neural Network is also known as a simple Convolution Neural Network. Shallow Convolution Neural Networks are mainly for image classification. This model after data processing and GLoVE word embedding can be used for identifying fake news. The Shallow Convolution Neural Network has an input layer that takes the input. The word embedding layer to implement GLoVE word embedding and the Dense layer are used for model prediction .

2. Long Short Term Memory

Long Short Term Memory is a recurrent neural network. It solves the RNN problem of long-term dependencies where RNN cannot predict the word stored in the long term memory. The layers involved in fake news detection are the input layer, word embedding layer, Dropout layer, LSTM layer, Dense Layer. The activation function used for the LSTM layer is ReLU. The activation function for the Dense layer is sigmoid. The loss function used is binary cross-entropy and the optimizer is Adam.

3. Gated Recurrent Neural Network

A gated recurrent unit (GRU) is similar to long shorter memory (LSTM) unit but without an output gate. GRU's solve the vanishing gradient problem by using an update gate and a reset gate. The function of the update gate is to control the information that flows into memory. The purpose of reset gate is to control the information that flows out of memory. The GRU has following layers that are input layer, word embedding layer, Dropout layer, GRU layer, Dense layer. The optimizer used is the Adam optimizer and the loss function is the binary cross-entropy.

4. Convolution Neural Network with Long Short Term Memory $(CNN + LSTM)$

Convolution Neural Network with Long Short Term Memory incorporates the features of both Convolution Neural Network and Long Short Term Memory. The $CNN + LSTM$ has the following layer for implementation they are the Input layer, GLoVE word embedding layer, Dropout Layer, Convolution Layer, MaxPooling layer, LSTM layer with Batch normalization, Dense layer. The optimizer used for hyper parameter tuning is the Adam and the loss function is the binary cross-entropy.

5. Deep Convolution Neural Network

Deep Convolution Neural network has a structure similar to Shallow Convolution Neural Network. The term Deep in the Deep Convolution Neural network describes that the model is made deeper by increasing the number layer. For detecting fake news efficiently the model has more number of Convolution and Dense layers. The Deep Convolution Neural Network has filter size of 128, kernel size 5, and stride of size 1. The optimizer is the Adam optimizer and loss function is the binary cross-entropy. The activation function for the Convolution Layer is ReLU and the Dense layer is sigmoid.

6. Multi-Channel Convolution Neural Network

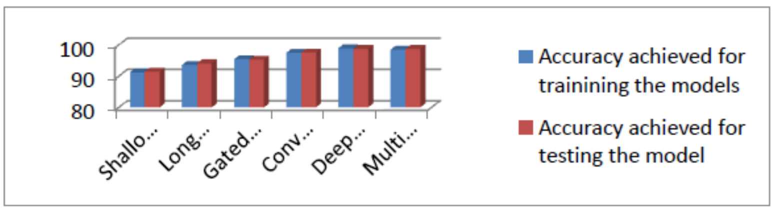
Multi-Channel Convolution Neural Network is a special type of Convolution Neural Network. Multi-Channel Convolution Neural Network involves using standard Convolution Neural Network with different kernel sizes. The different kernel sizes used are 4, 6, and 8. Multi-Channel Convolution Neural Network merges the different Convolution layers having varying kernel size for efficient detection of fake news. In the model developed since individual convolution layers are used, all the flatten layers are merged and passed as input to the Dense layer. The activation function used is RELU. The last dense layer uses a Sigmoid Activation function that is used to find the fake news from real. The loss function used is binary cross-entropy and the optimizer is Adam.

III. Performance Results

The metrics for evaluating deep learning models is accuracy. Accuracy is described as the number of instances correctly identified from all the instances present. The two datasets after splitting into 80 % training and 20 % testing data are evaluated with the different deep learning models and the accuracy of the model over two fake news datasets is determined. The model which provides high training and testing accuracy is determined as the best for identifying fake news. The accuracy is determined by running the different hyperparameters through the model for 20 epochs

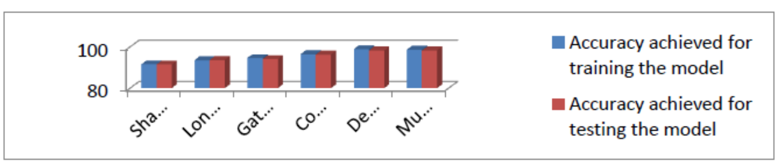
$$\text{Accuracy} = \frac{\text{Correctely Predicted observations}}{\text{Total Number of observations}}$$

The accuracy of different deep learning models to detect fake news for dataset 1 that is Getting Real about Fake news is as shown in the bar graph.



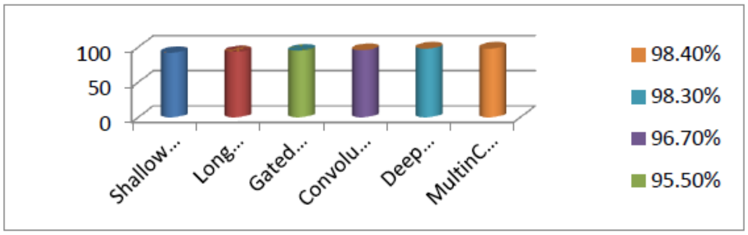
The Training and Testing Accuracy of Deep Convolution Neural Networks and Multi-Channel Convolution Neural Network is above 98%. The accuracy of the Convolution Neural Network with Long Short-Term Memory and Gated Recurrent Neural Network is 97% and 95% respectively. The accuracy of LSTM and Shallow Convolution Neural Network is less than 94%.

Dataset 2 that is COVID 19 fake news dataset is used to determine the accuracy of various deep learning models. The training and testing accuracy is as shown in the bar graph below.



The Training and Testing Accuracy of Deep Convolution Neural Networks and Multi-Channel Convolution Neural Network is above 98%. The accuracy of the Convolution Neural Network with Long Short-Term Memory and Gated Recurrent Neural Network is 97% and 95% respectively. The accuracy of LSTM and Shallow Convolution Neural Network is less than 94%.

The bar graph shows the best accuracy achieved by different deep learning models over the two datasets. From the overall best accuracy it is proved that Deep Convolution Neural Network and Multi-Channel Convolution Neural Network deep learning model shows the best performance results in identifying fake news from real news.



IV. Conclusion and Future Scope

In this paper, two datasets are used and the performance of deep learning models in detecting fake news is explained through performance results. The results show that the versions of the Convolution Neural Network that is the Deep Convolution neural Network and Multi-channel Convolution Neural Network shows high training and testing accuracy and can be used efficiently for detecting fake news. These deep learning models work well even for the latest dataset that is the Covid-19 dataset. The model can be further elaborated by used advanced methods such as GANs with different high versions of word embedding to achieve higher accuracy and better results.

References

[1] Kaliyar and Rohit Kumar, Fake news detection using a deep neural network In 2018 4th International Conference on Computing Communication and Automation (ICCCA), IEEE (2018), 1-7.

[2] Thota, Aswini, Priyanka Tilak, Simrat Ahluwalia, and Nibrat Lohia, Fake news detection: A deep learning approach. SMU Data Science Review 1(3) (2018), 10.

[3] Qian, Feng, Chengyue Gong, Karishma Sharma and Yan Liu, Neural User Response Generator: Fake News Detection with Collective User Intelligence, In IJCAI, (2018),

3834-3840.

[4] Yang, Yang, Lei Zheng, Jiawei Zhang, Qingcai Cui, Zhoujun Li and Philip S. Yu, TI-CNN: Convolutional neural networks for fake news detection. arXiv preprint arXiv:1806.00749 (2018).

[5] Zhang, Jiawei, Bowen Dong, and Philip S. Yu. FAKEDETECTOR: Effective Fake News Detection with Deep Diffusive Neural Network, (2018).

[6] Girgis, Sherry, Eslam Amer and Mahmoud Gadallah, Deep learning algorithms for detecting fake news in online text. In 2018 13th International Conference on Computer Engineering and Systems (ICCES) IEEE (2018), 93-97.

[7] Ruchansky, Natali, Sungyong Seo and Yan Liu, CSI: A hybrid deep model for fake news detection, In Proceedings of the 2017 ACM on Conference on Information and Knowledge Management (2017), 797-806.