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Performance Analysis Of Deep Neural Network Algorithm With Optimizer For Rumour Detection

Subhash Chandra Yadav[1], Pushpendra Kumar[2], Virendra Kumar[3]

[1,2,3]Department of Computer Science and Technology,Central University of Jharkhand, Ranchi, India

Email: scy123@gmail.com[1], pushpendra7589@gmail.com[2],virendracs44@gmail.com[3]

Abstract: Social networking sites and social media are vital sources of diverse nature of information. Enormous amount of data is floating per second in cyberspace through the internet. Numbers of social media applications are used to propagate and maintain the information. In most of the cases, these applications are also being used to spread false information and rumours that affect the individual and the society abruptly. In order to reduce the harmful impacts of rumour an automated rumour detection system is required. Several efforts are being made and various mechanisms have been developed to find out authenticity of information and dispel rumors on social networking sites by assessing their content and social circumstances with machine learning and deep learning approaches. In this paper, we have performed a comparative analysis of two deep learning models LSTM and BiLSTM with Adam and RmsProp optimizers to detect and track the rumour or non-rumour text from the given dataset.

Keywords: Social Media, RumourVerification, Deep Learning, LSTM, BiLSTM.

1. INTRODUCTION

The use of social media has exponentially increased over the years due to availability of internet connection. Most of the people are actively and frequently using the services of social media. Social media apps are gaining popularity among the masses for sharing their feelings, event’s information, personal information and social information. Plenty of users are using it to follow events, activities and breaking news. Spreading rapid information and news is one of the characteristics of social media[1]. As a result, social media has greatly changed people's way of interaction with each other and even their living style. Although social media platforms are rapidly being utilized to collect information and news; but due to an un-moderated nature (unchecked at the time of posting) of these messages , it may also lead to the panic situation in the society by spreading rumors[2]. Rumour can be defined as a story or declaration whose truth value is unknown or intentionally untrue[3]. False rumours are harmful because they provoke public panic and social instability, resulting in city turmoil. That's why it is extremely important to debunk rumours at their early stages of spread to minimize their negative consequences. Manual detection takes time to detect the kinds of rumour in social media.

Misinformation and fake news are used to spread the rumours, if they are not verified before propagation that may lead to severe consequences. Then the reliability of social media becomes doubtful, while there is a need to disseminate accurate information.

Due to this growing demand of social media platforms among the peoples to get news and information. There is a big scope for researchers to study the aspects related with information exchange and rumour dissemination. Researchers are using NLP, Data Mining[4] and other related tools and techniques to rate the authenticity and automaticity of rumors. Proposed work is focused on identifying the problems related with automatic social media rumour detection system due to its ever-increasing, non-structural, incomplete and noisy nature of data floating on the social media. Various models have already been developed to authenticate the rumour. Here we are performing the comparative analysis of some popular models of Deep Neural Network algorithms to construct a rumour classification model such as LSTM and BiLSTM with Adam and RmsProp optimizers.

2. **RELATED WORK**

This section contains literature surveys on rumour detection, and presents a brief discussion on prominent works done by many subject experts and leading researchers.

Gorrell*et* al[5]targeted to validate fake news automatically by using deep learning and machine learning.They have classified the given source claim in a conversational thread into stance classifications. This approach give better result and that's why Elena kochkina et.al got first rank in of the RumourEval 2019.This approach will perform well for short text. Which is tested on "kwon" dataset et al 2017, it contains 51 real and 60 fake rumour. The analysis is based on support, deny and query which is made intelligently by the algorithm.
Chen et al[6]focus on deep attention models based on the recurrent neural networks (RNN). RNN based approach can learn long range dependencies of contextual fluctuations in posting series. They used recurrence to implement a deterministic soft-attention technique that captures high duplicacy. This approach takes input from a set of relevant post series and is divided into time intervals and forms batches and aims to detect rumour at event level.
Li et al[7] proposed a paper based on the last two subtasks i.e stance detection and rumour detection rather than the four-subtask considered by Zubiaga et al (2018a) for the rumour resolution process. And it is mainly based on veracity classification. They used user credibility features derived from user profile and incorporated these features to the rumour detection layer and detection process uses attention mechanism they should pay more attention to the credible users and attention-based LSTM is used for more important text.
Ma et al[8]applied the idea to unified multitask models, understanding common features from both rumour detection and stance classification tasks. This is attained using a multi-layer recurrent neural network, which uses a common layer and a specific task-oriented layer. The overall sharing structure for RNN-based multi-task learning influenced their model's inspiration. They attempt to combined optimize both the task based on multi task framework unified neural. And they propose RNN based deep architecture in two layers, one is a shared hidden layer and other is an extra task specific hidden layer. They employ GRU instead of LSTM to represent hidden units.

Liu and Wu[9] proposed a unique technique to identify bogus information on social media by early analyzing. They create a time series classifier that combines RNN and CNN, with the goal of capturing global and local fluctuations in user characteristics, as well as the propagation path. It is the first time a multivariate time series is used to model the propagation structure. The proposed model is more broadly applicable and robust in detecting fake news early on.

Kochkina et al[10]proposed a model which is a LSTM based sequential model that concluded modelling the conversational structures of tweets and gaining an accuracy of 0.784 on the RumourEval test set. The key problem here is the classification of tweets in terms of the veracity of rumours spreading in the context of headline news on the Twitter conversations. The exploiting the conversational structure of threads for classification of stance and present a novel approach based on LSTM to attach conversations. In this approach the tree structure of conversation is decomposed into linear sequences for stance classification.

3. RESEARCH METHODOLOGY

In this research work the deep learning paradigm has been used to learn and fuse multi-modal features automatically. It does not require any feature engineering since the classifier learns and obtains the required feature during the training phase. Hence we have applied the Deep Learning paradigm such as LSTM and BiLSTM models for rumour detection with maximum accuracy. The control flow of LSTM is similar to that of RNN as it processes data and passes information; whereas it differs only in operation within the LSTM's cells[11]. The heart of LSTM is the memory state and its gates. As information travels in the sequence chain, the memory state acts as a communication highway that transfers relative information to the next stage. It's possible to conceive because of cell state and the network's "memory". In theoretical concept, the memory cell can carry important data throughout the sequence processing. When fact or data travel through the cell state, it is decided by the gate that it should be passed to next stages or not. Gates has several neural networks. During training, gates should identify/learn which information is important to keep or forget. Bidirectional LSTM often known as a BiLSTM[12]. It is a sequence processing model that contains two LSTMs, one of which takes input in a forward direction and the next one takes input in a backwards direction. BiLSTMs improve the context provided to the algorithm by increasing the amount of knowledge to the network. It understands which words come before and after a word in a phrase, knowing what words immediately follow and precede a word in the sentence. Framework for rumour detection is shown in figure 1.

This framework describe that we have taken socially available rumours and then we have applied data preprocessing such as stop-word removal, filtering, stemming etc. and got preprocessed text data and then preprocessed text data input to the LSTM or BiLSTM model and then LSTM or BiLSTM model classify these text and as a result it produced rumour, and non rumour text.

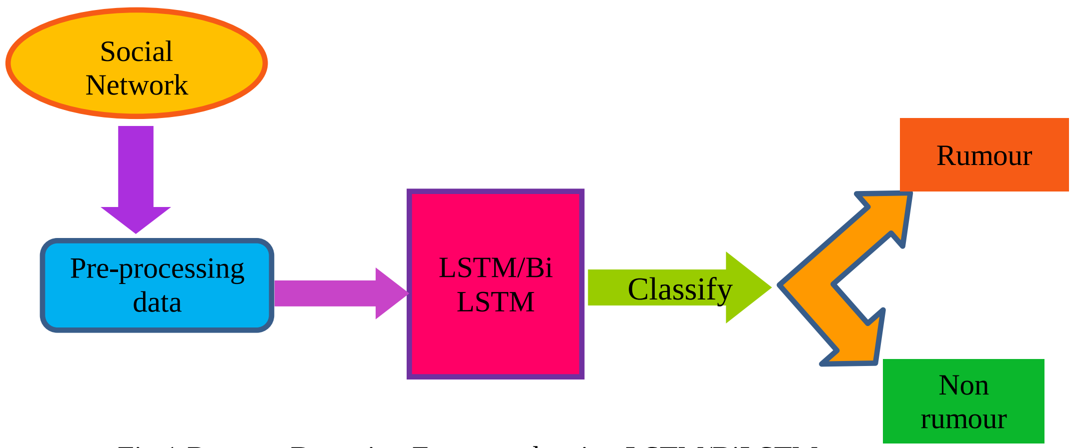

Fig 1:Rumour Detection Framework using LSTM/BiLSTM

4. RESULT AND DISCUSSION

This section represents the results obtained by applying by LSTM and BiLSTM models with maximum accuracy for rumour detection. Along with brief discussion on the dataset, different performance measures, and experimental results.

4.1 Dataset

In this experimental work we have utilized a dataset that is publicly available on kaggle[13]. This dataset consists of 20,800 rows and five columns (i.e id, title, author, text and label). Classified tweets are labelled with positive and negative text based on the different emotions used by the users. Table 1 shows the attribute description of dataset.

Table 1: Dataset Description

Attributes	Description
id	the news article's unique identifier.
title	the news article's title
author	news article's author
text	the article's text; may be to incomplete
label	the label that identifies an article as potentially (1 for untrustworthy, 0 for trustworthy)

4.2. Performance Measures

Confusion Matrix: A confusion matrix summarizes the various consequences of the prediction (**Table 2**)[14, 15]. Accuracy (Acc), Specificity(Spe), Sensitivity (Sen), Precision (Pre), false-positive rate (FPR) and false-negative rate (FNR) are calculated to verifythe model based on confusion matrix (**Table 3**).

Table 2: Confusion Matrix

		Actual	
		Rumour	Non-Rumour
Predicted	Rumour	TP	FP
	Non-Rumour	FN	TN

Table 3: Performance measures

Accuracy(Acc)	$(TP+TN)/(TP+FP+TN+FN)$
Specificity(Spe)	$(TN)/(TN+FP)$

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Sensitivity (Sen)	$(TP) / (TP + FN)$
Precision (Pre)	$(TP) / (TP + FP)$
False-Positive Rate (FPR)	$1 - Spe$
False-Negative Rate (FNR)	$1 - Sen$

4.3 Experimental Results

The dataset contains 20800 records, in which 10413 number of records having labelled with 1(rumour) and 10387 records having labelled with 0(non-rumour). Among all the records some of the records contain a null value, and because of this accuracy will be suppressed. So that we need to remove the record that contains the null value from the dataset. 18285 records remain after removal of records containing the null value from the dataset, in which 7924 records having labelled with 1(rumour) and 10361 records having labelled with 0(non-rumour). Converting the sentence into one-hot representation, 5000 is taken as vocabulary size. We split the dataset into training and testing in which 67% of data is randomly selected for training and the remaining 33% for testing the model. During the training, we applied the heat and trial method for selecting the number of epochs and batch size and we found that for 10 epochs and 64 batch sizes, the accuracy is much better i.e. approximately more than 90%. The confusion matrix of predicted results are shown in Table 4 to Table 7 for LSTM with Adam optimizer, LSTM with RmsProp optimizer, BiLSTM with Adam optimizer and BiLSTM with RmsProp optimizer respectively. Figure 2 shows the loss function while training the LSTM model and figure 3 shows the accuracy function of the LSTM model. Similarly figure 4 shows the loss function of BiLSTM and figure 5 shows the accuracy function of BiLSTM model.

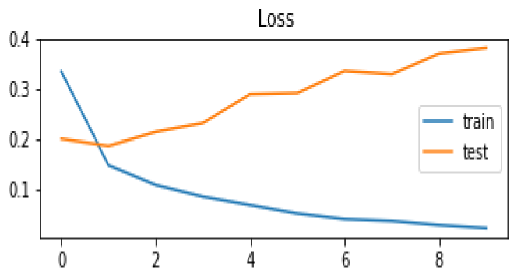


Figure 2: Loss Function of LSTM Model

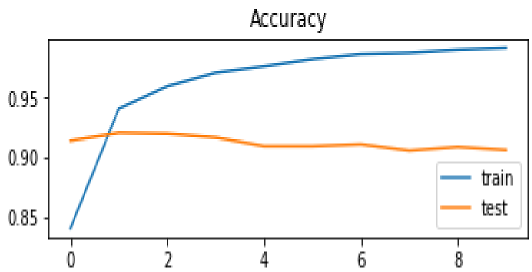
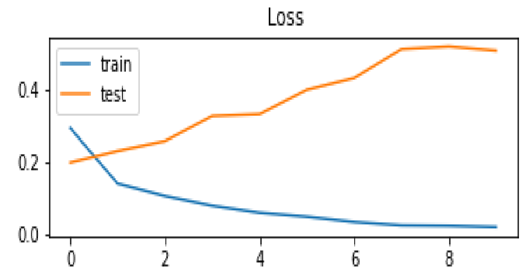


Figure 3: Accuracy Function of LSTM Model



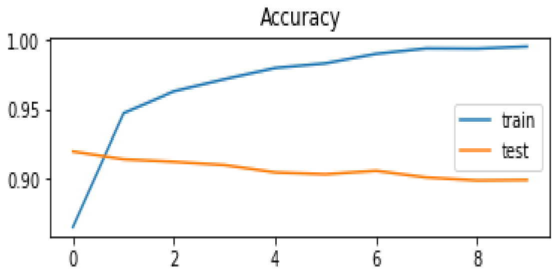


Figure 4: Loss Function of BiLSTM Model Figure 5: Accuracy Function of Bi LSTM Model

Table 4: Confusion Matrix for LSTM with Adam optimizer

		Actual	
		Rumour	Non-Rumour
Predicted	Rumour	3104	315
	Non-Rumour	238	2378

Table 5: Confusion Matrix for LSTM with RmsProp optimizer

		Actual	
		Rumour	Non-Rumour
Predicted	Rumour	3146	278
	Non-Rumour	206	2410

Table 6: Confusion Matrix for BiLSTM with Adam optimizer

		Actual	
		Rumour	Non-Rumour
Predicted	Rumour	3146	273
	Non-Rumour	273	2343

Table 7: Confusion Matrix for BiLSTM with RmsProp optimizer

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		Actual	
		Rumour	Non-Rumour
Predicted	Rumour	3136	283
	Non-Rumour	245	2371

The experiment conducted for detecting rumour for all specified evaluation measures are presented in Table 8 and Table 9. From Table 8 we observe that LSTM with Adam optimizer has 90.84%, 88.30%, 92.88%, 90.79%, 11.70% and 7.12% of Acc, Spe, Sen, Pre, FPR and FNR respectively whereas LSTM with RmsProp has 91.99%, 89.66%, 93.85%, 91.88%, 10.34% and 6.15% of Acc, Spe, Sen, Pre, FPR and FNR respectively. From Table 6 we conclude that LSTM with RmsProp produces better results than LSTM with Adam.
Table 9 shows that BiLSTM with Adam optimizer produces Acc 90.84%, Spe 88.30%, Sen 92.88%, Pre 90.79%, FPR 11.70% and FNR 7.12% whereas BiLSTM with RmsProp optimizer produces Acc 91.99%, Spe 89.66%, Sen 93.85%, Pre 91.88%, FPR 10.34% and FNR 6.15%. It can also be seen from Table 9 that BiLSTM with RmsProp optimizer produces a better result than BiLSTM with Adam.

Table 8: Comparative analysis of different optimizer for LSTM Model

Sl. No.	Measure	Adam	RmsProp
1	Acc	90.84	91.99
2	Spe	88.30	89.66
3	Sen	92.88	93.85
4	Pre	90.79	91.88
5	FPR	11.70	10.34
6	FNR	7.12	6.15

Table 9: Comparative analysis of different optimizer for BiLSTM Model

Sl. No.	Measure	Adam	RmsProp
1	Acc	90.94	91.25
2	Spe	89.56	89.33
3	Sen	91.99	92.75
4	Pre	91.99	91.72
5	FPR	10.44	10.67
6	FNR	8.01	7.25

After observing all the comparative analysis of Table 8 and Table 9 over the LSTM and BiLSTM model, the performance measures of LSTM is a little better than the performance of the BiLSTM model. So here we conclude that all performance measures are dependent on dataset used for training and testing and parameters values used in the model as BiLSTM represents a better model than the LSTM.

5. CONCLUSIONS

It has now become a trend to use social media and its related features for gathering information, facts, and news around the world. Even in this social media dominated society, individuals are more interested to seek the information related with the public opinion regarding any fact/tweet/claim and also anxious to share their own feelings on social media; irrespective of the authenticity and truth of information. Under such circumstances early identification of rumour is the best way to prevent the bad effect of fake information dissemination on the society through social media plateform. Analysis of deep learning models such as LSTM and BiLSTM for detecting and tracking the rumour or non-rumour text from the given dataset and after performing comparative analysis we observe that the performance of LSTM is better thanBiLSTM . Further we can say that performance measures entirely depend on the dataset and parameters values used in the model's training.

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