

Feature-Based Learning Model for Fake News Detection and Classification

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ABSTRACT

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A social media adoption is important to provide content authenticity and awareness for the unknown news that might be fake. Therefore, a Natural Language Processing (NLP) model is required to identify the content properties for language-driven feature generation. The present research work utilizes language-driven features that extract the grammatical, sentimental, syntactic, readable features. The feature from the particular news content is extracted to deal with the dimensional problem as the language level features are quite complex. Thus, the Dropout layer-based Long Short Term Network Model (LSTM) for sequential learning achieved better results during fake news detection. The results obtained validate the important features extracted linguistic model features and are combined to achieve better classification accuracy. The proposed Drop out based LSTM model obtained accuracy of 95.3% for fake news classification and detection when compared to the sequential neural model for fake news detection.

Keywords : Buzz News, Dropout layer, Fake news, Long Short Term Network Model, Social media

I. INTRODUCTION

The internet is a part of all our daily lives and the sources of information are generated by various users. Due to social networks or the media, fake news gets more viral through the internet and creates various issues. An extensive time is required for modeling the entire fake news which requires more amount of time

to extract the news from the relevant elaborate dataset [1, 2]. There is a generation of more new messages and articles over the internet which can be fake news as it relates to the topics that are read continuously [3]. Extensive growth in social media has witnessed spies and the news obtained from social media gains popularity as the fake news becomes viral [4]. The lack of professional competence nowadays

creates traditional news platforms [5]. The fake news and the anomalous information are different from the truthful signals is a challenging part [6]. Thus, advanced computing technologies deal with various information which has a distinct meaning for the context [7]. The fake news data consists of high dimensional data which are massive in size and thus the effectiveness of the proposed research needs to be improved using deep learning models [8]. The deep learning models were extensively studied in the existing researches including the Convolution Neural Network, Long Short Term Memory (LSTM) model were immensely applied but failed due to the heterogeneous nature of unknown text data. The existing model resolved the statistical user behavior, to deal with social networking properties that include syntactic and semantic features [9]. The proposed method will consider the most prominent features such as syntactic and semantic for fake news content detection which provides promising results to overcome the source of the fake news problem. The proposed method characterized the fake news from the content where the linguistic features were extracted. Thus the fake news are characterized by the linguistic feature of the content.

The organization of this paper is as follows. Section 2 discussed the literature review of the existing models which have undergone for fake news detection. Section 3 describes the proposed Dropout LSTM model and its process. Section 4 describes the results and discussions in terms of quantitative and comparative analysis. Finally, section 5 describes the conclusion and future work.

II. LITERATURE REVIEW

Anshika and Anuja [11] developed a Linguistic Feature-based Learning model for Fake news detection and classification. The developed model utilized Horne2017 and Fake news data repository that consisted of BuzzFeed Political News Data. The developed linguistic model utilized the content-based

properties which generated the language driven features. These features were related with sentimental, grammatical, syntactic features that consisted of particular news. The Linguistic model required an approach that utilized handcrafted features that handled the time consumption problems that overcame the dimensionality problem. The sequential neural model resulted and compared to the existing models LSTM based approach detected the fake news in terms of precision. However, an extensive parameter features were required to improve the model performance and different approaches were required that utilized to solve various news detection problems.

Jozef Kapusta and Juraj Obonya et al., [12] performed a fake news classification of fake news based on Morphological Group Analysis. The developed model collected a unique dataset that consisted of various articles from news portals where the fake publishers mislead the news as fake. The developed model utilized decision trees for classification that evaluated the success rate among two distinct methods defined by the success rate. The decision trees generated 112 records and among them, 48 records were utilized that reflected on improving performances in terms of accuracy. However, the machine learning algorithm still required input datasets to create them and still more articles failed to consider the model when the percentage of accuracy was lowered.

Mohammad et al., [13] developed a Convolutional Neural Network (CNN) with margin loss for fake news detection and discerning fake news detection based on the individual content was difficult. An automatic fake news detection approach was utilized to prevent which mandatorily spreads the false information. The developed CNN with Margin loss function utilized different embedding models for the fake news detection. The static word Embedding with non-static Embedding provided the possible incremental up and updated word embedding for the training phases. These results showed that the fine-tuning embedding was utilized for data training but

failed to improve the model performance to enhance the embedding quality due to large-sized dataset.

Huang et al., [14] developed an Ensemble Learning Model Based on Self-Adaptive Harmony Search Algorithms (SAHS) for fake news detection. The developed ensemble learning model combined four different models called embedding Long Short Term Memory (LSTM), depth LSTM, Linguistic Inquiry and Word Count (LIWC) Convolution NN, and N-gram CNN was developed for fake news detection. The fake news was detected based on the optimized weights that fed to the ensemble learning model and SAHS algorithm. However, the optimization of weights using the SAHS algorithm was benefited by SAHS training and SAHS testing of a similar dataset. The developed model failed to detect fake news on social media at an early stage for news propagation.

Chenguang et al. [15] developed Cross-Modal Attention Residual and Multichannel CNN (CARN) for multimodal fake news detection. The developed multimedia technology was ignored with more social media news that consisted of information with different modalities such as videos, pictures, and texts. The CARN extracted the relevant information that maintained the modality for the unique information from where the Multichannel CNN mitigated the influence of noise information. The noise information was generated by cross-modal fusion component extracted the textual feature representation from original and fused textual information simultaneously. However, the multimodal fake news detection was a challenging task that failed to fuse the information among different modalities that were affected by the noise information lowered performance of the model.

III. Proposed Method

Each news on the system is carefully examined and the ones that are not fake or not news-worthy are deleted. The flow diagram of the present research work is shown in figure 1. Initially, the dataset BuzzFeed News is considered for the research and are undergone preprocessing to perform tokenization, stemming, stop word removal. The preprocessed data

will be undergone for the feature extraction process using WordNet lemmatization, Snowball stemmer, and word Cloud to obtain the terms that are prominent for classification. These terms are converted into vectors and are fed for the classifier for the process of classification. The news is classified as whether the news is fake or real.

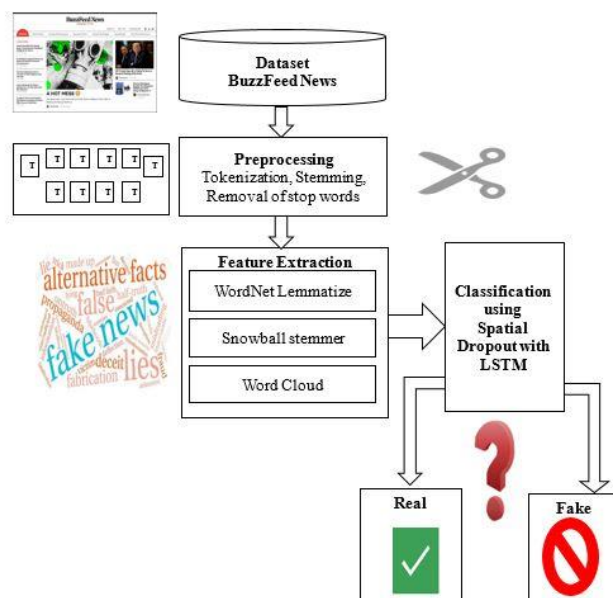


Fig. 1. Block diagram of the proposed method

Data Collection

The news considered from the dataset is examined carefully and the news that is not newsworthy or fakes are deleted by the human expertise. The news content and its keywords are extracted in a small time gap. The specified key words is generated with its respective time span which forms a query. The datasets have been used to detect fake news using the BuzzFeedNews dataset for evaluation. The information present in the dataset is downloaded using the below link :

<https://www.kaggle.com/kumudchauhan/fake-news-analysis-and-classification>

- Real and fake news content: It contains attributes like title, news id, text, authors, sources for each of the news information.
- News and user engagement: This property of the dataset will specifically state how many times the news articles are shared by the user.

- User–user relationship: This particular property will specify the user network present on social media.

The news source consists of news articles of 182 has the various number of fake news. The BuzzFeed – Web consists of a fake news corpus that has a total of 16 and out of that 9 publishers are chosen as an output in a week. Among the selected 9 publishers, 6 prolific hyper-partisan ones are considered with three mainstream publishers. These publishers have obtained a blue checkmark which is obtained from face book’s publishers that indicated the blue checkmark and authenticity obtained elevated the status within the network model. Every post are linked with the new articles which have 9 publishers was fact-checked based on the BuzzFeed professional journalists. Around 1,627 articles were verified that consisted of 826 mainstream, 545 rightwing, 256 left wing. The categories among the imbalance results differ from publication articles using BuzzFeed dataset. The imbalanced categories include 91 publication frequency articles and the number of users of BuzzFeed of 152,57.

i	Title	Text	Author	Label
0	House Dem Aide: We Didnâ Even See Comeyâ Let...	House Dem Aide: We Didnâ Even See Comey â Let...	Darrell Lucus	1
1	FLYNN : Hillary Clinton , Big Woman on	Ever get the feeling your life circles the	Daniel J. Flynn	0

	Campus - ...	rou...		
2	Why the Truth Might Get You Fired	Why the Truth Might Get You Fired October 29, ...	Consortiumnews.com	1

Pre-processing

- **Removal of stop words**

The stop words are those that have little meaning and not so important such as "is", "an", "the", etc are the other enterprise. These stop words are indexed with the platforms when the fetching of stop word resulted from the database are opposite to the user queries. The stops words are removed from the text often are removed before text training using deep and machine learning models. The present research work has utilized several NLP libraries that controlled the stop word removal. After the removal of the unimportant terms, the terms are required to be converted into tokens before transformed into vectors.

- **Tokenization**

The conversion of text to tokens before transforming to vectors is known as the process of Tokenization. The tokenization helps to filter out the unnecessary tokens in the case of documents that are converted initially to paragraphs and later into words. The given text generated will be broken into tokens and these tokens are individual phrases or words that are a whole sentence. The characters like punctuation are eliminated and the input tokens usually act as an input to process the text mining and parsing. Almost every Natural language processing task uses some sort of tokenization technique and it is vital to understand the pattern in the text. The tokens are important to generate the patterns that are the basic step for

processing the stemming and lemmatization process that generated the inflected words from the root obtained by the process of tokenization.

- **Stemming**

In the stemming process, removing of suffix present in a word brings to a generation of a base word. The process of stemming is similar to that of the normalization process which lowers the number of required computations. In the NLP, the stemming process requires a library like Snowball stemmer, WordNet Lemmatize, Word Cloud etc. The simple words like walk, walk, waited, waiting are similar words but contextually expressed differently. The present words will remove the suffix and considers only the base word as 'walk' from all the words.

- The rule-based approach has the process of stemming that slices inflected words at the suffix such as "-ing", "-ed", "-es", "-pre", etc as they are not useful.
- The two errors that are occurred during the process are over-stemming and under stemming approaches

Feature Extraction using Stemming

The process of reducing the documents based on the word stem affixes to suffixes prefixes to roots of words are called a lemma. The simple stemming process reduced the words as base words where similar words come under a common stem. The rules are constructed and will vary based on the dependent words. If the words are ending with the suffix 'ed' those words will be stemmed only with the base words and thus the process of stemming depends on the suffix terms.

1) Defining Snowball Stemmer

A snowball programming is used to support python language was developed an advanced version for Porter Stemmer is used to stem a better version as the stemmer fixes the issues. The snowball stemmer is

better when compared to the porter stemmer, which is represented as porter 2 stemming algorithm.

2) WordNet

The WordNet is known as the publicly available lexical database to establish the semantic relationships among the structured words. The lemmatization process is done with the earliest process that lemmatizes commonly lists comprehension. and the above wordnet is simple for using the WordNet lemmatizing on the words taken from the sentences. The words are corrected and are provided with the part of speech (POS) as the second argument for lemmatize. Similar words might have multiple lemmas based on meaning or context that can manually provide the POS tag correctly for every large text of data. Therefore, the correct tag of POS for each word maps right to the input characters accepts and passes for the next argument lemmatize.

3) Word Cloud

The word clouds are utilized for the frequent words where the prominent words are displayed as a body text. The word clouds analyze the low cost from the online survey that showed the performance of coding faster. A tag cloud is a visual design formed by a weighted list and the text data are represented typically for keywords. The meta data depictions from the websites visualize the free form of a text. The word cloud forms graphical representation for word frequency terms which provides prominence for words more frequently for the source text. If the word is larger, the more common words are present in the document visually.

Classification using Drop out layer with LSTM Network

In Keras model, GRU in addition to Accelerated Generic Adaptive Method is used as the proposed model. The Gated Recurrent Unit (GRU) model is used to develop the abstractive summarization and also performs the gating approaches for RNN. The

GRU acts as LSTM that includes forget gate but the performance of GRUs will execute better for a smaller range of datasets as well. The GRU primarily controls the gating network signals based on the previous memory. The signals obtained from the previous memory are used as an input that updates an activation state based on the current state of GRU. The present gating state has the weights are updated and adapted during the learning phase. The LSTM architecture has an input gate, an output gate as well as the forget gate. The forget gate is used to facilitate the remembering values in the cell based on the arbitrary time. The gates facilitate the flow of information in and out of cell control. The block diagram of the LSTM model is shown in figure 2. The output generated by the LSTMs can support the automated feature learning by extracting only the relevant features for the classification.

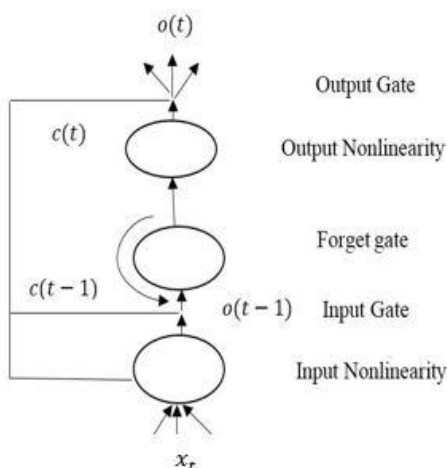


Fig. 2. LSTM model

The architecture has a full gated units operating with several variations as the data uses the hidden state from the previous state. The combinations generated are simplified into a form called a minimal gated unit. The hidden state of an LSTM cell can be calculated using equation 5. The layers of LSTM are calculated using equations 1 to 4.

$$i_t = \sigma(x_t U^i + h_{t-1} W^i) \tag{1}$$

$$f_t = \sigma(x_t U^f + h_{t-1} W^f) \tag{2}$$

$$o_t = \sigma(x_t U^o + h_{t-1} W^o) \tag{3}$$

$$C_t = \sigma(f_t \times C_{t-1} + i_t + C_t)$$

$$h_t = \tanh(C_t) \times o_t \tag{4}$$

Here,

i is known as input gate

f is known as forget gate

o is known as an output gate

W is known as a recurrent connection from the past hidden layer to the current hidden layer,

U is known as the weight matrix which connects the inputs to the current hidden layer.

The Keras implementation of LSTM updates includes parameter information that pertains or retains the overall state of the network. The information obtained from the previous states to the current input states are reflected on the latest state variable of the network. Moreover, all the adaptive parameters update the involved components of the internal state of the system. Additionally, the neural network process is also used to extract the summary based on the computational procedure such as forward and backpropagation processes. In the process of forwarding propagation, all the signal inputs are processed in the forward direction for the network layers' activation as input to output. An error value is estimated and calculated to connected weight and bias terms. The ANN model has 3 layered FFN networks which is discussed in the present section. However, the LSTMs has an issue as it overfits the training data easily that reduces the predictive skills. From an input connection, the dropout is applied for the LSTM nodes means the given probability has the data on the input connection for each of the LSTM block is excluded from the weight updates to the node activation.

An input signal is produced initially to obtain a training pattern that is presented in the network is multiplied with the weight values. Each of the bias terms will be added to the corresponded weighted signals and are imported to suitable activation functions which develop output and a hidden layer. The weighted values obtained based on error values

are summed and are added as an output neuron. The input layer and an output layer is explained in the following section based on the below process.

Input Unit:

The input unit is mathematically expressed in Equation (5)

$$o_i^1 = y \quad (5)$$

Hidden Units:

The hidden unit equation is expressed in Equation (6) and (7)

$$o_i^2 = f(\text{net}_i), i=1, \dots, I \quad (6)$$

$$\text{net}_i = y \cdot w_i^1 + b_i \quad (7)$$

Where,

f is the sigmoid activation function.

Output Unit:

The Output unit equation is expressed in Equation (8)

$$N(y) = \sum_{i=1}^I (w_i^2, o_i^2) = \sum_{i=1}^I (w_i^2, f(w_i^1, y + b_i)) \quad (8)$$

The designed neural architecture is a pro-type model and some minor changes are needed to overcome the fractional problem.

The Keras mentioned with the argument has dropout that is created in an LSTM layer. The range percentage for dropout will lie between 0 to 1 where 0 (no dropout) and 1 (no connection). The dropout process is the regularization method from where the recurrent connections and inputs to the LSTM networks for improving the network performance. Thus, the overfitting problems are reduced and are improved to the model performance was computationally lowered for deep learning techniques regularization. Dropouts remove or drops the input variables from the data samples was in turn updated on the activation function based on the previous layers. A large number of networks are simulated for the effect as distinct network structures turned on making the network nodes robust for the inputs. The

dropout rate is 0.3 for the present research work and the rate defines the probability for input retaining.

IV. Results and discussion

The results of the proposed Bi-GRU model with Gaussian noise layer are simulated by Anaconda navigator and Python 3.6 software with Windows 10 operating system. The proposed GRU model with Gaussian noise layer was implemented in a system consisting of 128 GB RAM, 1 TB memory, configured with RTX 2080 Ti GPU, and i9 processor operating at 3 GHz. The parameter settings for the proposed Drop out layer with LSTM is given in Table 1:

Performance measures

In this research work, the proposed Drop out layer with LSTM is compared with a benchmark model to validate the overall performance which is evaluated in terms of the below-mentioned major parameters like F-measure, accuracy, precision and recall.

1. Precision

Precision is the measure of truly positive tweets that are determined using the recall function with respect to the class c_i which is shown in equation (12)

$$\text{Precision\%} = \frac{|\text{Tweets correctly classified to class } c|}{|\text{Total tweets in class } c|} \times 100 \quad (12)$$

2. Recall

A recall is the number of relevant tweets classified divided by the total number of existing relevant tweets which is computed by using equation (13)

$$\text{Recall\%} = \frac{|\text{Tweets correctly classified to the class}|}{|\text{Total number of existing relevant tweets}|} \times 100 \quad (13)$$

3. Accuracy

Accuracy is the closeness of measurements to a specific value which is explained in equation (14).

$$\text{Accuracy\%} = \frac{|\text{Total number of correctly classified tweets}|}{|\text{Total number of tweets}|} \times 100 \quad (14)$$

4. F-score

F-score is defined as a combination of recall and precision which is shown in the following equation (15).

$$F - score\% = \frac{2 \times Precision \times Recall}{Precision + Recall} \times 100 \quad (15)$$

Quantitative Analysis

Three datasets such as Buzz news datasets are utilized for the evaluation of the performance of the proposed Dropout based LSTM network. The present research work examined for BuzzFeed Data that contain fake or real news from the social media and the contents filters the English languages and ignores the other regional language. The label for fake and real are manually labeled for the procedure received that has two separate folders. The present research requires a high memory bandwidth for each system and the cell fails to provide the hardware model for LSTM which is quite inefficient. Neural networks are a powerful tool but required more data for training when compared to the proposed Drop out based LSTM that considers all the input parameters for tuning them. Similarly, in the existing models, Bi-LSTMs effectively increase the amount of information available to the network which improves the context available to the algorithm. The Bi-LSTMs overcome the gradient vanishing problems considered the unstable behaviors for the process of training. The multilayer FFN or RNN propagated with useful information from the input and output end modeled the layers from an input end of the model. Therefore, both FFN and RNN models failed to obtain better performance measures. The proposed Drop out layer with LSTM will obtain better performances when compared to the existing LSTM, Bi-LSTM networks. In table 1, the results obtained for the drop out model in terms of accuracy, table 2 results obtained in terms of Precision, table 3 shows results in terms of Recall and table 4 shows results in terms of f-measure.

TABLE I. RESULTS OBTAINED FOR THE PROPOSED DROP OUT BASED LSTM MODEL IN TERMS OF ACCURACY

Accuracy	
Classifiers	BuzzFeed
LSTM	91.21
BiLSTM	93.46
Proposed	95.22

TABLE II. RESULTS OBTAINED FOR THE PROPOSED DROP OUT BASED LSTM MODEL IN TERMS OF PRECISION

Precision		
	BuzzFeed	
Classifiers	Fake	Real
LSTM	59	78
BiLSTM	68	79
Proposed	82	89

TABLE III. RESULTS OBTAINED FOR THE PROPOSED DROP OUT BASED LSTM MODEL IN TERMS OF RECALL

Recall		
	BuzzFeed	
Classifiers	Fake	Real
LSTM	85	48
BiLSTM	81	66
Proposed	88	83

TABLE IV. RESULTS OBTAINED FOR THE PROPOSED DROP OUT BASED LSTM MODEL IN TERMS OF F-MEASURE

F-measure		
	BuzzFeed	
Classifiers	Fake	Real
LSTM	70	60
BiLSTM	74	72
Proposed	85	86

Comparative Analysis

The temporal data information for the fake news detection examined the latent semantic feature detected the fake news to explore the variants for detecting the news. The main texts have information

such as social graphs user information etc and propagation paths but reduced the chances of fake news discrimination. The early detection of fake news on social media failed to detect the fake news at the early stage of news propagation. Whereas the proposed model utilized a dropout layer with LSTM for the classification of news as fake or real. The dropout layer has the property of selecting the number of features using dropout regularization from where the recurrent and input connections. This is done to the LSTM units excludes probabilistic from the weight updates and activators during network training. Thus the proposed method reduces the overfitting problems and the improvement in the performances is shown in table 5 and the graphical representation is shown in figure 3.

TABLE V. COMPARATIVE RESULTS OBTAINED FOR THE PROPOSED DROP OUT BASED LSTM MODEL IN TERMS OF ACCURACY

Methodologies	Dataset	Accuracy
LSTM based word embedding [11]	Buzz News Dataset	86.5
Embedding LSTM, depth LSTM, LIWC CNN, and N-gram CNN [14]		72.3
Proposed Dropout based LSTM		95.22

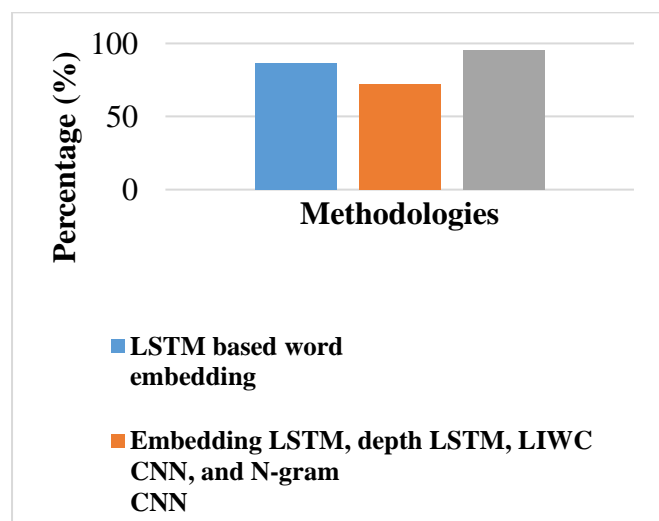


Fig. 3. Graphical representation for the proposed and the existing models.

V. Conclusion

The present work initially considers the features from the context and various computational techniques are used to extract the sentimental, syntactic,

grammatical, and readability features are fetched from the dataset having news. In the proposed work, the extracted feature sets were transformed into readable featured out the overall extracted features as per the study. The dropout-based regularization methods are utilized from where the recurrent connections and inputs to the LSTM networks improved the network performance. Thus, the overfitting problems are reduced and are improved with respect to the model performance was computationally lowered for deep learning techniques regularization. The preliminary experiments are conducted for performance validation that improves the accuracy up to 8 to 10 % for the model.

In the future, to reduce the spreading of fake news, identifying key features or elements that are involved in the spread of news is an important step. Likewise, real-time fake news identification in videos can be another possible future direction.

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