Unreliable User Detection by Applying Fake News Detection using Machine Learning

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Abstract: *The growth of social media has made it possible for any user to share and instantly express their opinions. Due to its damaging capacity to mislead individuals within society, fake news has recently attracted the attention of scholars. It has raised a troubling situation over the world. From a limited group of reputable and regulated sources to a variety of internet sources of news, the news industry has transformed. Because it has the potential to affect public opinion, fake news has a negative effect on society. This paper's primary goal is to identify the best model that achieves high accuracy performance. Fake news has an adverse impact on society since it may have an impact on public opinion. It is essential to look into the credibility of news reports that are published on any media platforms. In this paper, we present a machine learning-based fake news detection method based on user credibility. The experimental results shows that our model acquires an accuracy of 99% which is 2% improvement over existing approach.*

Keywords: Fake News, Detection, User Credibility, Machine Learning.

1. Introduction

People may now easily share content and communicate with others on social media because of the rise of smartphone usage. Social media has thus become more popular as a platform for the consumption of diverse news stories. A significant amount of data is generated online every day on different social media sites. [1][2][3]. The vast majority of the web data that is produced is information-based, particularly news-based [4][5][6][7][8]. The amount of fake headlines has increased as a result of how simple it is for users to share news online. Fake news [9] is defined as information that is released falsely with the purpose to mislead people. In order to look real and reputable, fake news or unreliable user is produced, and as a result, users readily share it on social media. Such news is published with the intention of gaining financial and political advantage and has the potential to affect public opinion. Since this has a significant effect on society, it is essential to address this issue [10][11][12][13]. Figure 1 illustrates each level of fake news detection. At the creation step, fake news is produced by one or more sources for defined propaganda. Fake news can be produced outside of social media or within it. The headline and the body are the two primary components of the news. Images, publications, and news sources are examples of other potential components. One or more authors must upload the fake news to social media after developing it. In this case, the publisher uses that social networking sites.

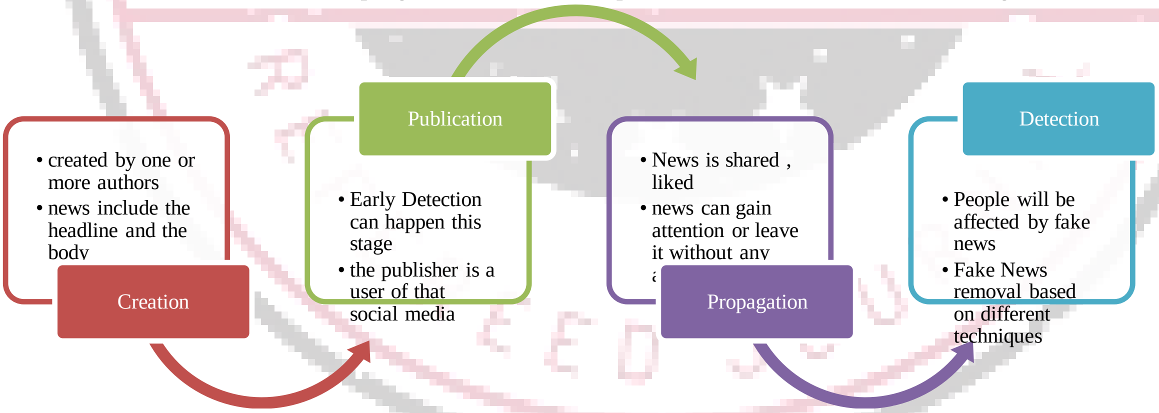

Figure 1. Stages of Fake News

The detection of fake news is an issue that affects society today and is now getting a lot of attention from the research world as well. The fact that a number of organizations are engaged in creating and disseminating fake news, in addition to the lack of public knowledge and the complicated propagation across social media, makes it difficult to identify fake news [14]. It is the primary cause of journalists' disregard for reputation damage to others in favour of financial benefit. Because there are so many different fake news propaganda outlets, this issue is challenging. [15]. The construction of useful features from a variety of sources, such as textual content, user profile data, and news diffusion patterns, was the major emphasis of early research on fake news detection [16]. It has been investigated how to distinguish between fake news and real news using linguistic traits [17] such writing styles, sensational headlines, and textual analysis [18]. In addition to linguistic features, several research suggested a variety of content-based approaches [19] and various feature-based approaches [20] regarding the news dissemination. These feature-based methods, however, take a long time to create, are biased, and need a lot of work.

2. Literature Review

Many recent research [21][22] use different machine and deep learning based approach to automatically train high-level models for fake news identification to address the previous issues. For example, ML [23], DNN [24], and neural networks [25] are used to learn how to interpret content. These techniques just use additional information types to identify fake news, giving little emphasis to early detection. Furthermore, in fact, these models are unable to identify fake news at the first stages of news since they only take all or a fake percentage of repost content into account. Some research [26][27][28] investigate ways to identify fake news before it spreads by relying on a small number of postings. The primary problem in these approaches is that they fail to recognize how crucial user and publication reputation is in detecting fake news at an early stage [29][30][31].

Jarrahi et al. [1] suggested a method called CreditRank for assessing the credibility of publications on social networking sites. They also recommend FR-Detect, a highly accurate multi-modal system that uses both user-related and content-related information to identify fake news. In order to correctly connect publishers' features with latent textual content features, a sentence-level CNN is also provided. According to experimental findings, the publishers' features may boost the accuracy and F1 efficiency by up to 16 and 31 percent, correspondingly. Additionally, publishers' actions in various news industries have been statistically examined and analyzed. According to Kaliyar et al. [9], user-based interactions and echo chambers of individuals who have the same opinions may be very beneficial in detecting fake news. Therefore, for the purpose of identifying fake news, they have concentrated in this research on the news article's content and the existence of echo chambers in the social network. Due to one‘s unsupervised nature and use primarily with conventional ML models, standard factorization methodologies for fake news detection have a limited effectiveness. A deep neural network (the suggested model) was used to classify on news content and social context-based information separately as well as together, with the help of the best hyper-parameters. A real-world fake news dataset from BuzzFeed and PolitiFact has been used to verify the effectiveness of our suggested strategy. According to classification results, our suggested method had a validation accuracy of 92.30 percent. The findings validate the possible application of the approach for categorizing fake news and demonstrate considerable improvements over the current state-of-the-art algorithms in the domain of fake news identification. Mangal and Sharma [14] determined the veracity of the news, an unique method using CNN+ LSTM has been developed. In this study, image visual feature with news text feature and headline texts were compared to find the effective result. For this, 1000 images were taken into account with the headline texts, in which 367 news were fake and 633 news were real. The accuracy of the proposed method is 91.07 percent . The outcome suggests that the novel methodology is superior to the cutting-edge method. Mansouri et al. [16] suggests a method based on LDA+ CNN. The purpose of this study is to use deep convolutional neural network to identify fake news. The approach uses a CNN to target either unlabelled or labelled input in a semi-supervised learning environment. This approach begins by utilizing CNN to extract numerous characteristics from text and image data. In order to determine the classes of unclassified data, linear discrimination analysis (LDA) is then performed. In order to improve the impact of the predicted class within every step, the fitness function has also been altered. Findings show that the suggested approach, which has a precision value of 95.5 percent, works better than other approaches in term of accuracy, precision, and sensitivity. Konkobo et al. [17] developed a semi-supervised learning technique to quickly identify fake news on social media. It enables the model to handle the large volume of unlabelled data on social networking sites by employing semi-supervised learning. Then, using the CredRank Algorithm to assess users' credibility, researchers built a small network of users who participated in the dissemination of a specific piece of news. Initially, researchers constructed a model to retrieve users' comments posted in replies. To test the model, researchers used the real-world datasets Politifact and Gossipcop. SSLNews achieves an accuracy of 72.25 and 70.35 percent. Some of the recent contributions are presented in table 1.

Table 1. Recent Contribution in Literature Review

Author	Dataset	Method	Merits and Demerits
Rachna et al. [2]	ban fake news	LSTM+RF	• Captured the important hidden clues and information in the source tweet text. • Achieved ~63% of accuracy. • Accuracy rate was quite low. • User profile and textual features were not discussed here.
Kao et al. [4]	Twitter15 & Twitter16	Multi-view attention networks	• Captured the important hidden clues and information in the source tweet text. • Achieved ~93% of accuracy. • The model cannot analyzed the reply or comments on the tweets.
Verma et al. [5]	BuzzFeed News	WELFake	• Word Embedding Over Linguistic Features were used. • Achieved 96% of accuracy. • Knowledge graphs and user credibility were not considered.

Shahbazi and Byun [6]	BuzzFeed News	NLP and Blockchain	• Adopted NLP for fake news detection. • Achieved MAPE of approx. 1.87. • Latency was very high (~1500ms). • RMSE was very high (~318).
Xu et al. [18]	BuzzFeed News	Latent Dirichlet Allocation	• Domain Reputations and topic of news was observed. • Real and fake similarity was observed. • Textual analysis was not performed.
Sansonetti et al. [19]	Data taken from PolitiFact.com	Deep Neural Network	• Unreliable users were detected on social media on the basis of questionnaires. • Nearly 93% of accuracy was achieved. • Learning Loss rate was high.

3. Methodology

In this work, we are going to design a framework for fake news identification. For this user profile and their activities are observed. With their activities, and profile information correlation we are going to detect fake or real news as well as user. For this analysis statistical feature engineering and deep learning is integrated together in common framework, as presented in figure 2.

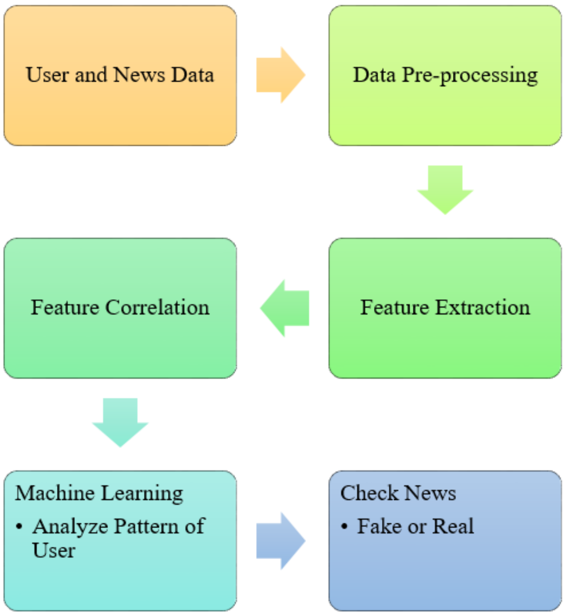

Figure 2. Flow Chart of Proposed Work

The entire work is performed in following steps:

3.1 Data Collection

In this step, dataset will be created of different users for fake news detection as a reference to some secondary dataset available. Fake News detection was collected from Kaggle [41].

3.2 Data Pre-processing

Data pre-processing is a critical step of natural language processing, such as fake news detection, as it directly impacts the model's effectiveness to the complexity of the data. Fake news datasets consist of many links, hashtags, special symbols, etc. Therefore, we applied many steps of pre-processing to each dataset.

These steps are as follows.

• Lower casing: The most effective kind of text pre-processing is lowercasing, which ensures correlation within the feature set and solves the sparsity problem.

• Removal of URL's: Irrelevant links embedded into news have been removed.

• Removal of special symbols such as punctuations, emojis, ,,, ’, ¨ , #, $, %, & etc.

• Removal of Stop Word: Stop words are small words in a language that are useless in text mining and are utilised to structure language grammar. These stop words have been filtered away, including articles, conjunctions, prepositions, some pronouns, and common terms like the, a, an, about, by, from, to, and so on.

• Tokenization in pre-processing is the process of dividing lengthy text sequences into tokens (i.e., smaller pieces). For example, consider this sentence before tokenization: ‘‘Fake news dataset’’, after tokenization it comes ‘Fake’, ‘news’,’ dataset’.

• Stemming The stemming step is the process of changing the words into their original form. For example, the words ‘‘ Walking’’, ‘‘ Walked’’ and ‘‘Walker’’ will be reduced to the word ‘‘walk’’.

3.3 Feature Extraction

N-gram with TF-IDF are used to extract features for the ML models and build feature matrix. To describe the context of the text, we employed several sizes of N-gram approach, ranging from n = 1 to n = 4 (i.e., uni-gram, bi-gram, trigram, and four-gram). TF-ID assigns a weight to each word representing the importance of the word in the document and corpus.

Word embedding is a technique for converting text data (words) into vectors. Every word is represented as an n-dimensional dense vector, with vectors that are comparable for similar words. We used the Glove [35] for word embedding to build embedding matrix. GloVe is an unsupervised learning technique that generates word vector representations. The resulting representations highlight intriguing linear substructures of the word vector space, which are trained using aggregated global word-word co-occurrence statistics from a corpus. We utilised glove.6B.zip, which contains vectors in four different dimensions: 25d, 50d, 100d, and 200d. The embedding matrix was constructed using 200d vectors.

3.4 Feature Correlation

In this step feature correlation is performed on statistical tools such as chi-square etc. This identifies the related features that are useful for classification of news or posts reality.

Chi-Square: If you have 2 categories of variables from a population, you use this analysis. It has been used and sees if there was a substantial link or correlation between the two variables. We will use the latter of the two kinds of chi-square tests: chi-square goodness-of-fit and the chi-square test for independence. In the chi-square test, the dof is determined as (n-1)*(m-1) wherein n and m are the numbers of columns and rows, correspondingly. It is mathematically represented as:

$$\chi_c = \sum \frac{(Oi - Ei)^2}{Ei} \qquad (1)$$

Where,

Degree of freedom is given by c,

Observed value by O and expected value by E

3.5 Learning and Classification

In this step, deep learning user pattern is analyzed which determines the reality of news or posts provided by user. In this step, deep features were extracted and selected using LSTM network which is further classified using voting classifier. Long Short Term Memory Networks is an advanced RNN, a sequential network, that allows information to persist. It is capable of handling the vanishing gradient problem faced by RNN. A recurrent neural network is also known as RNN is used for persistent memory. At a high-level LSTM works very much like an RNN cell. Here is the internal functioning of the LSTM network. The LSTM consists of three parts, as shown in figure 3 and each part performs an individual function. The first part chooses whether the information coming from the previous timestamp is to be remembered or is irrelevant and can be forgotten. In the second part, the cell tries to learn new information from the input to this cell. At last, in the third part, the cell passes the updated information from the current timestamp to the next timestamp.

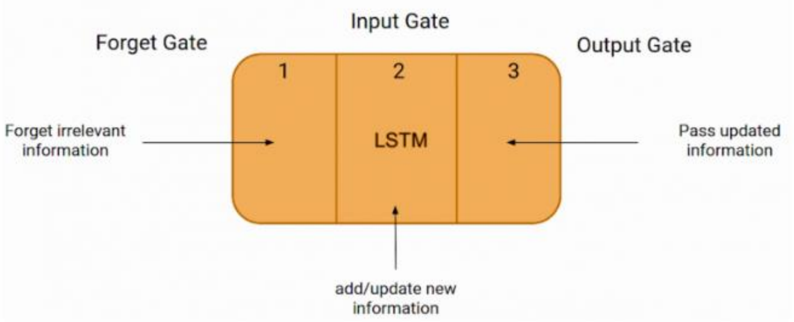

Figure 3: LSTM Architecture

Just like a simple RNN, an LSTM also has a hidden state where H(t-1) represents the hidden state of the previous timestamp and Ht is the hidden state of the current timestamp. In addition to that LSTM also have a cell state represented by C(t-1) and C(t) for previous and current timestamp respectively.

By using a majority voting strategy, better accuracy as compared to the simple classifier. The classifiers used for designing the MV algorithm are Support Vector Machines (SVM), Random Forests Classifier and extreme Gradient Boosting.

4. Result Analysis

This section shows the simulation results. The simulation scenario is created and simulated for performance evaluation of proposed algorithm. In order to evaluate the performance of proposed algorithm scheme, the proposed algorithm is simulated in following configuration: Pentium Core I5-2430M CPU @ 2.40 GHz, 4GB RAM, 64-bit Operating System, Python Platform.

Performance Parameters used are:

Accuracy: It is one of the most important parameters for determining the classifier's performance. It denotes the total number of accurately categorized real news. The mathematical expression of accuracy is given in eqn (2):

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (2)$$

Precision: It's calculated as the ratio of properly identified fake or real news to the total number of news, and it's given by:

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}) \quad (3)$$

Recall: Recall is the ratio of true positive (TP) to them sum of false negative and true positive.

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN}) \quad (4)$$

F-Measure: The F-Measure is the result of harmonic mean of precision and recall rates.

F-Measure= 2 * [(precision * recall) / (precision + recall)] (5)

Here, TP stands for True Positive. (This is the overall test samples that are anticipated to be real news and whose true label is also real).

TN stands for True Negative. (This shows overall test samples that are expected to be fake news and whose true label is also fake).

FP stands for False Positive. (This is the overall test samples that are anticipated to be real news but are actually labelled as fake news).

FN stands for False Negative. (This is the total value of test samples that are projected to be fake news but are actually labelled as real news).

Dataset Description: Fake News detection was collected from Kaggle [32]. There are 3988 news articles in this dataset. In addition to the body of the text, each article includes a headline and a list of URLs. There is also a class label with the values ‘‘0’’ for fake news and ‘‘1’’ for real news. Only the article body and headline can be used in models. The 1868 articles are real news, while the remaining 2120 are fake news. The statistics of the dataset are presented in figure 4.

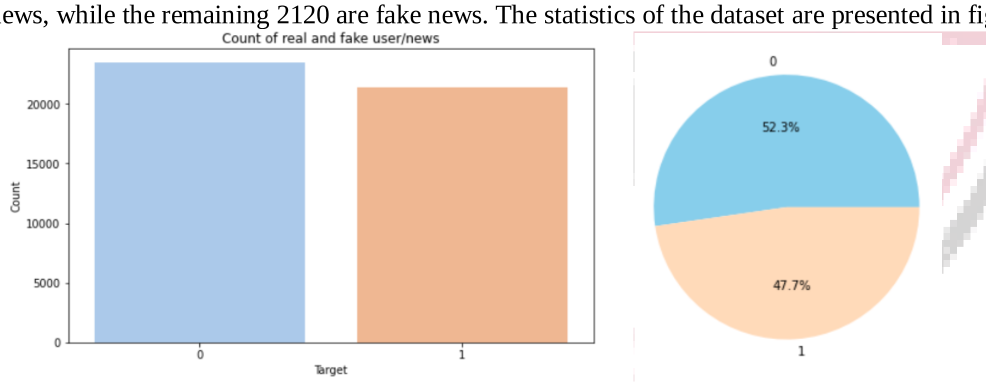

Figure 4: Dataset Distribution

Table 2 shows Testing Performance of Model without Feature Correlation for fake ,real and overall. The accuracy,precision,recall,F1_score is 93.8%,94%,94%,94% for fake data respectively, 94.6%, 94%, 94%, 94% for Real data respectively and 94%, 94%, 94%, 94% for overall respectively. Table 3 shows Testing Performance of Model without Feature Correlation for fake ,real and overall. The accuracy, precision, recall, F1_score is 99.5%, 100%, 99%, 100% for fake data respectively, 99%, 99%, 100%, 99% for Real data respectively and 99%, 100%, 99%, 99% for overall respectively.

Table 2: Testing Performance of Model without Feature Correlation

	Accuracy	Precision	Recall	F1-score
Fake	93.8%	94%	94%	94%
Real	94.6%	94%	94%	94%
Overall	94%	94%	94%	94%

Table 3: Testing Performance of Model with Feature Correlation

	Accuracy	Precision	Recall	F1-score
Fake	99.5%	100%	99%	100%
Real	99%	99%	100%	99%
Overall	99%	100%	99%	99%

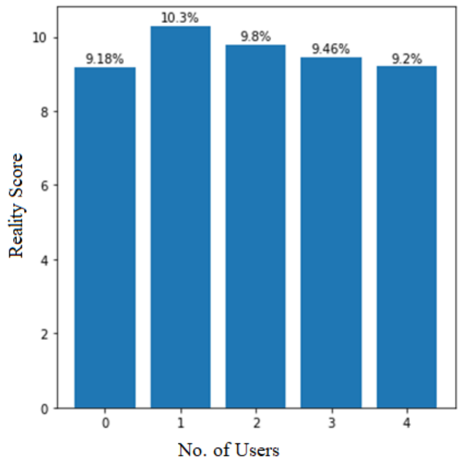

Figure 5. User Reality Score with respect to News Reality

Figure 5 shows user reality Score with respect to news reality (i.e., either fake or real) with No. of users are 9.18%, 10.3%, 9.8%, 9.46%, 9.2% respectively. Table 4 shows testing performance of model with and without feature correlation. The accuracy, precision, recall, F1_score is 99%, 100%, 99%, 99% for with correlation and without correlation 94%, 94%, 94% and 94 respectively. Figure 6 shows Testing Performance of Model with Feature Correlation like OPCNN-FAKE [12], LSTM+RF [13], CNN+ LSTM [14] and Proposed model have accuracy 97%, 63%, 97% and 99% respectively which shows our proposed model achieves higher accuracy as compared with other models.

Table 4: Performance Analysis with and Without Feature Correlation

	Accuracy	Precision	Recall	F1-score
With Correlation	99%	100%	99%	99%
Without Correlation	94%	94%	94%	94%

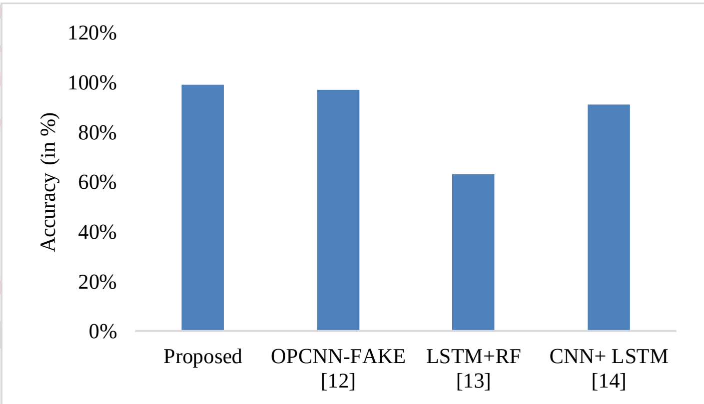

Figure 6. Testing Performance of Model with Feature Correlation

5. Conclusion

In this work, a framework is designed for news reality identification. For this user profile and their activities are observed. With their activities, and profile information correlation we are going to assign a reality score to each and every user. For this analysis statistical feature engineering and deep learning is integrated together in common framework to enhance the performance. The training datasets have been used to optimize and train the models, while the testing datasets were used to evaluate the models. The main aim of this paper is to find the optimal model that obtains high accuracy performance. The growth of media has made it possible for any user to share and instantly express their opinions. Due to its damaging capacity to mislead individuals within society, fake news has recently attracted the attention of scholars. Because it has the potential to affect public opinion, fake news has a negative effect on society. Investigating the reliability of news stories published on any media platforms is crucial. In this study, we provide a user credibility based fake news detection system using machine learning approach. The experimental results shows that our model acquires an accuracy of 99%, precision 100%, Recall and F1-score 99% respectively. This shows improvement of

2% on existing approach. It is important that we have some mechanism for detecting fake news, or at the very least, an awareness that not everything we read on social media may be true, so we always need to be thinking critically. This way we can help people make more informed decisions and they will not be fooled into thinking what others want to manipulate them into believing. In addition, we may use knowledge-based and fact-based approaches to detect fake news. We will also expand our planned dataset to include data from additional languages.

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