Detecting fake news spreaders on twitter

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ABSTRACT

Nowadays, fake news is prevalent and too simple to propagate through social media, particularly during elections and pandemics like COVID-19. Several fake news stories have appeared on social media sites like LINE, Facebook, and Twitter after the COVID-19 epidemic throughout the world. Also, a lot of older individuals simply forward these communications without checking their veracity, which speeds up the dissemination of fake information. So, our goal is to identify fake news using machine learning. In this paper, we describe a supervised method that automatically gathers a sizable but noisy training dataset made up of a significant number of tweets. We will categorize tweets during collection into trustworthy and untrustworthy sources, then using the dataset to train a classifier. The categorization of fake and real tweets is the next classification objective for which we apply that classifier. We first demonstrate that real news is larger in size, shared on Twitter for a longer length of time, and shared by people with more followers than following. Second, we employed machine learning models like support vector machine (SVM), random forest (RF), and decision tree (DT), and we found out that the SVM is the best of all the models due to its best results and 99% accuracy.

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1. INTRODUCTION

Fake news that is published on social media has gained a lot of attention recently. As a result, techniques for automatically recognizing fake news have drawn considerable interest using machine learning [1]. It is a simple binary classification issue to determine whether a news tweet is fake or not. Twitter posts have been categorized for a variety of purposes, most notably sentiment analysis, but also by kind (such as news, and memes) or relevance to a certain issue [2], [3].

In each of those scenarios, the quantity and caliber of training data have a significant impact on how well the classification model performs. Thus, assembling a sufficient number of training instances is a difficult challenge. While categorizing an emotion or topic can be done more quickly and accurately by crowd workers with less expertise [4], [5], determining whether a news tweet is false or not involves a lot more investigation and may not be an easy assignment. For instance, professional journalists are employed by websites like Politifact to report on fake news. Several organizations and countries consider fake news to be one of the biggest risks to our contemporary civilization. The term "fake news" has generated a lot of debate in recent years. There are several meanings, but none are recognized by everyone. It frequently includes ideas like deceit and manipulation. The term "fake news" will be used interchangeably throughout this paper, and its meaning will be limited to assertions that can be independently verified as untrue. In a similar vein, references to verifiably true statements will be made in real news.

One of the social media sites for user collaboration and communication is Twitter. Since its inception, the number of users has surpassed millions. Users tweet brief messages of 140 characters or fewer, along with images and videos, as the network's main channels for communication. Regrettably, the growth of social communication on Twitter has attracted hackers who take advantage of the trust between users to transmit dangerous information on the network, resulting in a significant number of victims [6], [7].

Fake information, whether purposefully or accidentally distributed, has grown increasingly common in recent years due to the dynamism of social media and the internet [8]. It is now harder than ever to distinguish between facts and views linked to economic or political upheavals. Fake news has been widely disseminated and has permanently altered individuals and society. This is a problem in our work that should be solved by Using a variety of natural language processing (NLP) and preprocessing methods, including tokenization, stop word removal, lemmatization, stemming, and machine learning algorithms like support vector machine (SVM) and random forest (RF), we create a model that can identify between fake news and true news. In order to choose the most accurate classifier on the dataset, we also assess the performance of these distinct classification approaches. Social media networking platforms primarily interpret news in three different ways:

– Text: Because many postings are posted in the form of texts, there has been a lot of study done on the computational linguistic analysis of texts, concentrating on the semantic origin of language systematically.
– Multimedia: A single post combines many media formats. Graphics, images, video, and audio can all be used. This is quite attractive since it draws visitors' attention without forcing them to read the material.
– Hyperlinks: By using hyperlinks, the author of the post may cross-reference to other sources, earning the viewers' confidence by demonstrating the post's provenance. Cross-referencing with other social networking sites and embedding images are also prevalent practices.

In this part, we go through some earlier research on fake news identification. Fake material that replicates news media content in form but differs in organizational method or goal is known as fake news. Several automatic fake news detection techniques have been developed in recent years. For instance, Siino [9] performed a post-hoc examination of layer output on the shallow CNN model, which had the best performance. They discovered parallels between the embedding space produced by CNN and the keyword dataset analysis. In the embedding space, there were two distinct clusters that represented the two classes, and their locations appeared to correspond to their keyness scores the further apart the tokens are from the other cluster, the greater the keyness score. Also, they examined the token windows with the largest and smallest local values after mapping the convolutional layer outputs to inputs. According to the article’s user class, they saw that the CNN filters assigned maximum values to several themes. Also, a contrast that they used between shallow and pre-trained models is looked at. Since it can handle the variability in users' feeds, it is likely that the shallow CNN works better. Moreover, a comparable sentiment analysis job has also found this pattern.

The bidirectional gated recurrent unit (BiGRU) model is the foundation for the bogus account detection system developed in [10]. In order to determine if a twitter user profile is real or fraudulent, attention has been placed on the content of users' tweets. The semantic and grammatical context of tweets are preserved by grouping them into a single file and utilizing the global vectors (GloVe) word embedding approach to convert them into a vector space. The findings are encouraging and confirm that utilizing GloVe with BiGRU classifier excels with 99.44% for accuracy and 99.25% for precision when compared to baseline models like long short-term memory (LSTM) and convolutional neural networks (CNN). The results produced with GloVe and Word2vec under the identical conditions were compared to demonstrate the effectiveness of their technique.

2. METHOD

There are types of fake news and patterns that help in detection, like visual-based fake news, some fake news items feature more visuals than actual content [11], [12], which may be doctored video, altered photos, or a combination of the two. Also known as user-generated news, this type of fake news is produced by phony sources and directed at certain audiences that may represent particular age groups, genders, cultures, or political affiliations. Knowledge-based, these entries provide scientific (or so-called scientific) explanations to various unsolved issues, giving the impression that they are real [13], [14]. For instance, natural treatments for the body's excessive blood sugar levels, style-based Style-based postings are written by fictitious journalists who replicate and impersonate the writing style of some legitimate journalists, and finally, stance-based postings present actual statements in a way that makes their significance and intent clear. This section outlines the proposed five-step process for identifying fake and real news on Twitter: text collection, text preprocessing, feature extraction, text collection, and then finally the classifier [15], [16]. In order to remove the noise from the fake news dataset, we created a preprocessing pipeline for each statement. The following three components make up the preprocessing pipeline:

a) Whitespace was used in lieu of characters that are not in the range of a to z or A to Z.
b) Changed all of the characters to lowercase.
c) Isolated the inflectional morphemes "ed", "est", "s", and "ing" from their token stem. For instance, verified is "confirm" + "-ed". Figure 1 demonstrates the steps of the technique used.

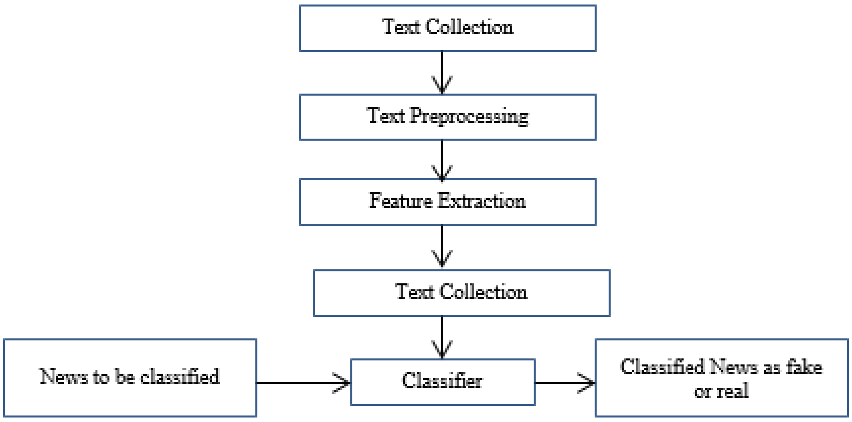

Figure 1. The steps of the method used for the detection procedure

News headlines and paragraphs are included in the data we utilize. The average length of each title is 12.45 words, but the average word count for each piece of content is 405.28. Because the contents are too long for us to train effectively [17], [18], in our project we just utilized the headlines for the fake news identification. Additionally, the text contains too many specifics and facts for a piece of news, which might confuse the models while they are being trained [19], [20]. Our paper's primary goal is to identify fake news by thoroughly analyzing user tweets. These layers will be described in more detail in the following sections.

2.1. The dataset

The ISOT fake news dataset is the one we utilize. It was presented by the ISOT Research Lab at the Canadian University of Victoria. It is a dataset, a collection of thousands of bogus news stories and genuine content, gathered from several trustworthy news websites and websites with a reliability warning at Politifact.com [21], [22]. The ISOT fake news datasets are used to carry out the text gathering procedure. Information is collected from 244 websites. It is composed of around 44.898 posts that were tallied during a 30-day period. The real news dataset is made up by 23.481 posts, whereas 21.417 posts make up the fake news dataset. The subject, date, and label are all necessary, along with the title and content in the news body. The news is broken down into a number of categories, such as "political news", "global news," "news and politics", "government news", "left news", "US news", and "Middle East". We used word clouds to illustrate this dataset with real and fake news, respectively, to get insight into it is shown in Figure 2. Figure 2(a) displays the word cloud for the real news in the dataset. Figure 2(b) demonstrates one of the dataset's fake news stories.

(a) (b)

Figure 2. Word clouds for real and fake news (a) real news in the dataset and (b) fake news in the dataset

In the word cloud for real news, we can see that "North Korea", "government", "New York", and "support" appeared frequently, while in fake news, "even", "twitter", "think", and "featured image" showed up most frequently. "Tuesday" appears frequently in real news but not in fake news. "Hillary Clinton" and "right" appear frequently in fake news but not in real news. We can get some crucial information to distinguish between the two groups of data from these two-word clouds. The dataset was originally two comma separated values (CSV) files, one containing fake news and the other real news. The dataset was merged, then divided into training, validation, and test sets using shuffles with a ratio of 64%:16%:20%. The distribution of the data in the training, validation, and test sets is shown in Table 1 for the original combined dataset, which comprises 44,898 data points.

Table 1. Data distribution

Training	Validation	Test
64.0%	16.0%	20.0%
28,734	7,184	8,980

2.2. Preprocessing of data

The major objective of this section is to preprocess the input data using NLP techniques in order to set up the subsequent stage of feature extraction. News headlines and texts are part of the data we utilize. The average length of each title is 12.45 words, but the average word count for each piece of content is 405.28. Because the contents are too long for us to train effectively [23], [24], in our project we just utilized the headlines for the false news identification. Also, the text contains much too many specifics and facts for a piece of news, which might confuse the models while they are being trained. In order to remove the noise from the false news dataset, we created a preprocessing pipeline for each statement. The following 3 components make up the preprocessing pipeline: replacing non-between-a-to-z or A-to-Z characters with whitespace; changing every character to lowercase; and removing the token stem from the inflectional morphemes "ed", "est", "s", and "ing". For instance, verified is "confirm" + "-ed". In order to train the model on a dataset with sentences of appropriate lengths and to exclude titles with an extreme length that would allow the model to fit on imbalanced data, we additionally clipped the titles into sentences with a maximum length of 42 [25], [26].

2.3. Models

We discovered that a variety of techniques, including machine learning (ML), deep learning (DL), and transformers, may successfully identify bogus news after researching relevant works regarding NLP. We build a model that distinguishes between fake news and real news by using various NLP and preprocessing techniques like tokenization, stop word removal, lemmatization, stemming, and machine learning algorithms like SVM and RF. We also evaluate the effectiveness of these various classification methodologies in order to select the best classifier for the dataset.

3. RESULTS AND DISCUSSION

Real news and fake news are evenly represented in our sample. Real news and false news, however, are not equally balanced in the actual world, as the dataset suggests. To mirror reality, we expected that there would be far more actual news than fake news. To compare the performance of each model, we ran two experiments using balanced and unbalanced datasets, respectively. We reduced the original false dataset to one-tenth of its original size to mimic the real-world situation in order to create the unbalanced dataset. The distribution of real and false data for the original training set, the unbalanced training set, the original validation set, the original test set, and the imbalanced test set is shown in Table 2.

Table 2. Imbalanced data

Data	Training set	Validation set	Test set
True	13,765	3,409	4,243
Fake	14,969	3,775	4,737

We utilized the most popular metrics to assess how well the models we built for the false news detection challenge performed, we evaluate and analyse the results based on these metrics for different datasets, clasisfiers and different methods of feature extraction metholdology:

- True positive (TP): Whenever phony news is indeed fake news as anticipated.
- True negative (TN): When it's foreseen, the news is accurate.
- False negative (FN): When forecasted, the news is false when it should be true.
- False positive (FP): When anticipated fake news becomes genuine news.

Based on the importance of the four conditions mentioned above, we may establish the following metrics.

$$\text{Precision} = \frac{|TP|}{|TP|+|FP|} \tag{1}$$

$$\text{Recall} = \frac{|TP|}{|TP|+|FP|} \tag{2}$$

$$\text{F1} = 2.\frac{Precision.Recall}{Precision+Recall} \tag{3}$$

$$\text{Accuraccy} = \frac{|TP|+|TN|}{|TP|+|TN|+|FP|+|FN|} \tag{4}$$

In the field of machine learning, these four metrics are the most often utilized, particularly for categorization issues. It enables us to assess a classifier's performance from several angles. Accuracy is typically the best representative statistic for the evaluation since it accurately captures the categorization scenario.

Table 3 shows the performance of the three distinct models we employed on the balanced and unbalanced datasets, using the various measures indicated above. The findings demonstrate that, for our false news detection challenge, training on unbalanced datasets performs marginally better than training on balanced datasets. The outcomes also demonstrate how much superior Transformer-based models are than the competition. Moreover, machine learning models with more characteristics outperform those with less features in terms of performance. In other words, SVM outperforms RF and decision tree (DT). The results displayed in Table 3 are prommising. While we must gain understanding about the models we implemented

Table 3. Performance on the dataset

Model	Accuracy	Precision	Recall	F1-score
SVM	0.994833	0.993287	0.995887	0.994586
RF	0.983697	0.986075	0.979622	0.982838
DT	0.986726	0.987256	0.984857	0.986055
RNN	0.993875	0.993517	0.993747	0.993632

4. CONCLUSION

In recent years, politics and national security have greatly benefited from the identification of false news. In this study, we discussed the use of suggested machine learning models (SVM, RNN, RF, and DT) for fake news identification on the ISOT fake news dataset. We used word embedding and preprocessing to create word sequences from the datasets, which we then entered into our models. Our models performed similarly in the experiments, but the findings clearly demonstrate that one model improves over another. SVM has the greatest results and performances in both datasets, making it the top model overall.

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REFERENCES

[1] H. K. Easa, A. A. Saber, N. K. Hamid, and H. A. Saber, "Machine learning based approach for detection of fake banknotes using support vector machine," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 31, no. 2, pp. 1016–1022, 2023, doi: 10.11591/ijeecs.v31.i2.pp1016-1022.

[2] E. Min *et al.*, "Divide-and-conquer: Post user interaction network for fake news detection on social media," *WWW 2022 - Proceedings of the ACM Web Conference 2022*, pp. 1148–1158, 2022, doi: 10.1145/3485447.3512163.

[3] B. Mukunthan, "Detection of malicious data in Twitter using machine learning approaches," *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, vol. 12, no. 3, pp. 4951–4958, 2021, doi: 10.17762/turcomat.v12i3.2008.

[4] M. B. Albayati and A. M. Altamimi, "An empirical study for detecting fake facebook profiles using supervised mining techniques," *Informatica (Slovenia)*, vol. 43, no. 1, pp. 77–86, 2019, doi: 10.31449/inf.v43i1.2319.

[5] T. Wu, S. Liu, J. Zhang, and Y. Xiang, "Twitter spam detection based on deep learning," *ACM International Conference Proceeding Series*, no. January 2017, 2017, doi: 10.1145/3014812.3014815.
[6] A. K. Ali and A. M. Abdullah, "Fake accounts detection on social media using stack ensemble system," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 3, pp. 3013–3022, 2022, doi: 10.11591/ijece.v12i3.pp3013-3022.
[7] K. R. Purba, D. Asirvatham, and R. K. Murugesan, "Classification of instagram fake users using supervised machine learning algorithms," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 3, pp. 2763–2772, 2020, doi: 10.11591/ijece.v10i3.pp2763-2772.
[8] L. K. Ramasamy, S. Kadry, Y. Nam, and M. N. Meqdad, "Performance analysis of sentiments in Twitter dataset using SVM models," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 3, pp. 2275–2284, 2021, doi: 10.11591/ijece.v11i3.pp2275-2284.
[9] M. Siino, E. Di Nuovo, I. Tinnirello, and M. La Cascia, "Fake news spreaders detection: Sometimes attention is not all you need," *Information (Switzerland)*, vol. 13, no. 9, pp. 1–22, 2022, doi: 10.3390/info13090426.
[10] F. Benabbou, H. Boukhouima, and N. Sael, "Fake accounts detection system based on bidirectional gated recurrent unit neural network," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 3, pp. 3129–3137, 2022, doi: 10.11591/ijece.v12i3.pp3129-3137.
[11] A. A. Ali and R. M. Shafi, "Test-retrieval framework: Performance profiling and testing web search engine on non factoid queries," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS).*, vol. 14, no. 3, pp. 1373–1381, 2019, doi: 10.11591/ijeecs.v14.i3.pp1373-1381.
[12] A. A. Saber, A. K. Omer, and N. K. Hamid, "Google pagerank algorithm: using efficient damping factor," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 28, no. 3, pp. 1633–1639, 2022, doi: 10.11591/ijeecs.v28.i3.pp1633-1639.
[13] A. A. Saber and N. K. Hamid, "Complex networks analysis: centrality measures," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 29, no. 3, pp. 1642–1647, 2023, doi: 10.11591/ijeecs.v29.i3.pp1642-1647.
[14] H. A. Santoso, E. H. Rachmawanto, and U. Hidayati, "Fake Twitter account classification of fake news spreading using Naïve Bayes," *Scientific Journal of Informatics*, vol. 7, no. 2, pp. 2407–7658, 2020, [Online]. Available: http://journal.unnes.ac.id/nju/index.php/sji.
[15] A. Imran, M. U. Ahmed, S. Hussain, and J. Iqbal, "Social engagement analysis for detection of fake news on twitter using machine learning," *Webology*, vol. 19, no. 3, pp. 1864–1880, 2022, [Online]. Available: https://www.webology.org/data-cms/articles/20220713114515amwebology 19 (3) - 126 pdf.pdf.
[16] F. Paquin, J. Rivnay, A. Salleo, N. Stingelin, and C. Silva, "Multi-phase semicrystalline microstructures drive exciton dissociation in neat plastic semiconductors," *arXiv preprint arXiv:1310.8002*, vol. 3, pp. 10715–10722, 2015, doi: 10.1039/b000000x.
[17] I. B. Abdullah, "Incremental PageRank for Twitter data using hadoop," *Technical paper*, pp. 1–58, 2010, [Online]. Available: papers2://publication/uuid/7B07AE25-2F4D-4C22-B085-043A18D15010.
[18] R. Kaur and S. Singh, "A survey of data mining and social network analysis based anomaly detection techniques," *Egyptian Informatics Journal*, vol. 17, no. 2, pp. 199–216, 2016, doi: 10.1016/j.eij.2015.11.004.
[19] M. Al-Qurishi, M. Al-Rakhami, A. Alamri, M. Al-Rubaian, S. M. M. Rahman, and M. S. Hossain, "Sybil defense techniques in online social networks: A survey," *IEEE Access*, vol. 5, pp. 1200–1219, 2017, doi: 10.1109/ACCESS.2017.2656635.
[20] S. S. Shree, C. Subhiksha, and R. Subhashini, "Prediction of fake Instagram profiles using machine learning," *SSRN Electronic Journal*, vol. 10, no. 3, pp. 1–6, 2021, doi: 10.2139/ssrn.3802584.
[21] M. Kwon, Y. S. Jeong, and H. J. Choi, "Feature embedding and conditional neural processes for data imputation," *Electronics Letters*, vol. 56, no. 11, pp. 546–548, 2020, doi: 10.1049/el.2019.4246.
[22] B. Hasan, S. Alani, and M. A. Saad, "Secured node detection technique based on artificial neural network for wireless sensor network," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 1, pp. 536–544, 2021, doi: 10.11591/ijece.v11i1.pp536-544.
[23] P. G. Pratama and N. A. Rakhmawati, "Social bot detection on 2019 Indonesia president candidate's supporter's tweets," *Procedia Computer Science*, vol. 161, pp. 813–820, 2019, doi: 10.1016/j.procs.2019.11.187.
[24] S. Gurajala, J. S. White, B. Hudson, B. R. Voter, and J. N. Matthews, "Profile characteristics of fake Twitter accounts," *Big Data and Society*, vol. 3, no. 2, pp. 1–13, 2016, doi: 10.1177/2053951716674236.
[25] A. Gupta and R. Kaushal, "Towards detecting fake user accounts in facebook," *ISEA Asia Security and Privacy Conference 2017, ISEASP 2017*, no. February, 2017, doi: 10.1109/ISEASP.2017.7976996.
[26] M. Swe and N. Myo, "Fake accounts detection on Twitter using blacklist," *Proceedings - 17th IEEE/ACIS International Conference on Computer and Information Science, ICIS 2018*, no. May, pp. 562–566, 2018, doi: 10.1109/ICIS.2018.8466499.

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