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A Review of Previous Research on Machine Learning, Deep Learning, and Natural Language Processing for Text-Based Fake News Detection

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Abstract

The spread of misinformation through text has become a critical problem in the current digital age, impacting public opinion and the credibility of the media. To maintain the integrity of information contained in texts, it is essential to identify and counter misinformation. This study examines twelve previous studies that employed machine learning, deep learning, and natural language processing methods to detect fake news in texts and were published between 2020 and 2024. The study aims to highlight the key techniques for identifying false news, assess their effectiveness, and pinpoint research gaps. The results demonstrated that whereas classic machine learning algorithms like SVM achieved an accuracy of 95.05%, deep learning models like BERT and BiLSTM produced higher accuracy, reaching up to 98.90%. The study also identified key challenges including a lack of standardized benchmarks, generalization issues, and data bias. In order to close these gaps and raise the precision and effectiveness of detection systems, the paper concludes by proposing directions for future research.

Keyword: Fake News Detection, Social Media, Deep Learning, Machine Learning, NLP.

Introduction

The distribution of false information has existed since the dawn of human civilization, but its spread has accelerated with the rise of social media usage rises and people's dependence on the Internet for information gathering grows. People frequently use information from the Internet to make decisions, and if the information is inaccurate or skewed, it can lead to poor decisions. These rumors greatly impact innocent people, subjecting them to online harassment, threats, and insults on social media, along with numerous real-life repercussions.

Given its substantial influence on people's lives, health is one of the primary issues with false news [1]. Numerous cancer patients have died prematurely as a result of false information on the Internet [2]. According to estimates, the first three months of 2020 saw almost 800 deaths from the coronavirus [2]. False information about the COVID-19 vaccine [3], [4], and the coronavirus [5] has led to the hospitalization of over 6,000 patients globally. In addition to damaging a company's reputation and generating revenues for its propagators, fake news can cause stock values to drop. Fake news spreads six times more faster than real news, which leads to fear and financial loss in society, according to [6].

Since there is no assurance of the credibility of fake news is credible, it has a detrimental impact on people and society [5], public opinion [7], and the decision-making process. Because of the vast volume of data, it is very challenging to manually identify fake news on social media. Therefore, it is crucial to identify and curb the spread of false information to preserve the integrity of news distribution on social media.

Fake news spreads across a wide range of fields, including marketing [8], finance [9], security [10], health [11], politics [12], and other industries. Defamation or causing harm are just two of the many motivations why people spread fake news. Another motivation is to attract more viewers for financial gain [13]. A further motivation is to spread mockery and deceive public [14].

This paper reviews the top studies in this field and determines the outcomes they achieved on various datasets to investigate advanced techniques, particularly machine learning (ML), deep learning (DL), and natural language processing (NLP), in detecting fake news within textual content. Automated text-based fake news detection systems reduce the time and effort required to identify false information [14].

This paper is organized as follows: The introduction section, discussing the background of the research problem and its significance in the context of fake news detection. Next, the related work section explores some existing research in the field of fake news identification. Finally, we present the conclusion and outline future work.

Related work

There are many recent research papers that have addressed the detection of fake news in texts published on social media using different techniques and datasets; we mention the most recent of these in 2020, a study by Annop et al. [15] proposed to find out the emotional nature of texts in order to identify fake health-related news. In their work, they used 1000 English texts divided into 500 texts classified as real and 500 texts classified as fake from the Health and Well Being (HWB) dataset. Five different models were used on this dataset. Naive Bayes got 79% of the answers right, K-Nearest Neighbour (KNN) got 92.5%, Support Vector Machine (SVM) got 90%, Random Forests got 84%, Decision Tree got 94%, AdaBoost got 96.5%, Convolutional Neural Networks (CNN) got 91%, and Long Short-Term Memory (LSTM) got 92%.

Sharma et al. [16] conducted a study on fake news detection to mitigate its harmful consequences. They utilized the LIAR dataset of 10,240 statements for the Static System and REAL-OR-FAKE. CSV dataset for dynamic systems. A set of algorithms, namely Bag-Of-Words, N-Grams, and TF-IDF, extracted the features from the dataset. In the Static System, Naïve Bayes, Random Forest, and Logistic Regression were used to classify the extracted features. In the Dynamic System, Passive Aggressive was used instead. The best performance was achieved in the static system by logistic regression, where they achieved an accuracy of 65% and an F1 score of 75%, and for the dynamic system, they got an accuracy of 92.7% and an F1 score of 92.6% by passive aggressive classifier. We divided the data into 67% training and 33% testing.

Reference [17] proposed the use of natural language processing (NLP) techniques to detect fake news from news headlines or content in social media. The features were extracted using N-gram and terms frequency inverse document frequency (TF-IDF). The training was done using four models in the Keras neural network. The first model is fed an N-gram vector consisting of news headlines; the second model is fed an N-gram vector consisting of news content; the third model receives vectors for news sequences, and the fourth model is fed vectors of news content sequences. Their methodology was applied to two Kaggle datasets, which were merged, resulting in 9,805 texts that were merged together. They obtained the best training accuracy by training on news content using the second and fourth models, which amounted to 90.3% and 90%, respectively. The dataset was divided into 80% for training and 20% for testing.

Reference [18] did a study on how to use a set of machine learning classifiers to find fake news. These include Naïve Bayes, Support Vector Machine (SVM), and Passive Aggressive Classifier. The features were found using the Term Frequency-Inverted Document Frequency (TF-IDF) technique. The study used a dataset of 6335 texts, and the Support Vector Machine (SVM) gave the best results, with an accuracy of 95.05% and an F1-Score of 93.14%. The dataset was divided into 80% train and 20% test.

As social media usage continues to increase, and this results in an increase in the sharing of fake news. Reference [19] presented a study on detecting fake news on social media using machine learning models. In this study, the following models were applied: We used the LIWC tool to get features from the images and then used Support Vector Machine (SVM), Logistic Regression, Multilayer Perceptron (MLP), K-Nearest Neighbours (KNN), Random Forest (RF), Voting Ensemble Classifiers, Bagging Ensemble, Boosting, Boosting Ensemble Classifiers, Bidirectional Long Short-Term Memory Networks (Bi-LSTM), Linear SVM, and Convolutional Neural Network (CNN). This research was carried out on four datasets, namely the ISOT Fake News dataset [20], consisting of 44898 articles that mainly target politics; the second dataset, DS2, available in Kaggle, consisting of 25,512 articles covering different aspects; the third dataset, also available in Kaggle, known as DS3, consisting of 3352 articles related to sports, politics and entertainment; and the fourth dataset is the sum of the articles present in the three pre-specified datasets to evaluate the performance of the models on the set of articles covering different fields. The highest accuracy was obtained for the first dataset by Random Forest (RF) and Perez-LSVM, reaching 99%, 99%, respectively. In the second dataset, the highest accuracy was obtained by both the Bagging classifier (decision trees) and the Boosting classifier (XGBoost). As for the third dataset, the highest accuracy was obtained by Perez-LSVM, reaching 96%. For the last dataset, the highest accuracy was obtained by Random Forest (RF) and is 91%.

With the continuous increase in the spread of fake news, especially regarding the COVID-19 pandemic, [21] presented a study to classify real and fake news on a dataset of 10,700 articles collected from social media. For the classification process, they used machine learning models, namely logistic regression, support vector machine (SVM), decision tree, and gradient boost, after extracting features using the TF-IDF algorithm. They achieved the highest accuracy of 93.32% with the SVM model.

Reference [22] published a study that used three datasets to find fake news in texts: RumourEval-19, which has 8,439 texts written in English; Weibo-16, which has 1,878,384 texts written in Chinese; and Finally, another dataset called Weibo-16, which has 1,989,802 texts written in Chinese. A group of transformer models were used in this study. The BiGRU model gave F1-Scores of 0.340, 0.826, and 0.855; the BERT model gave F1-Scores of 0.346, 0.867, and 0.915; and the NileTMRG and HSA-BLSTM models gave F1-Scores of 0.342, 0.908, and 0.932 for the three datasets.

Reference [23] proposed a study based on artificial intelligence techniques to detect fake news from texts. They achieved the best results with the FakeBERT model, which combined different blocks from the Convolutional Neural Network (CNN) with the BERT model. This was done after using GloVe to embed words in a dataset of 20,800 texts and getting a 98.90% success rate. This study also applied some machine learning models and obtained the highest Multinomial Naive Bayes (MNB), which is 89.97%.

Reference [24] also proposed a paper in which they presented a methodology for detecting fake news to combat it by using two deep learning models, BiLSTM and attention-based BiLSTM. The attention-based BiLSTM model achieved superior results over other models with an accuracy of 97.66% and an F1 score of 97.62%. This paper was applied to the WELFake [25] dataset consisting of 72,134 news articles, divided into 80% training and 20% testing.

Due to the increasing spread of fake news on social media and web pages, research is still ongoing in this field. Reference [26] presented a study in 2024 to detect fake news using machine learning classifiers, namely logistic regression, decision tree, k-nearest neighbour (KNN), naive Bayes, and support vector machines (SVM) after extracting features using TF-IDF and n-gram. They showed that TF-IDF achieves the best performance. In addition to these classifiers, they also used two deep learning models, namely Long Short-Term Memory (LSTM). These models and classifiers were trained on the Covid-19 dataset consisting of 948,373 tweets. They obtained the best accuracy using logistic regression at 95%, followed by SVM at 89% accuracy.

Reference [27] in 2024 proposed to detect fake news using machine learning models. The features were extracted using Term Frequency (TF) and Term Frequency-Inverted Document Frequency (TF-IDF) with N-gram and classified by a set of classification models, namely Support Vector Machines (SVM), K-Nearest Neighbour (KNN), Decision Trees (DT), Linear Support Vector Machines (LSVM), Stochastic Gradient Descent (SGD), and Logistic Regression (LR). They obtained the highest accuracy of 93.5% by TF-IDF with N-gram (N=1) classified by SGD on the Corpus dataset of 4233 satirical news articles [28]. They used both Grid Search CV and Random Search CV to tune the performance and get the best parameters for the SGD model, and the best accuracy was obtained by Random Search CV, which is 94.2%. The researchers divided the dataset into 80% train and 20% test sections.

Reference [29] suggested an automated way to find fake news using datasets like FakeNewsNet [30], BuzzFeedNews [31], which have 1627 articles, and LIAR16 [32], which has 12836 sentences. This study applied a set of deep learning models – BERT, GRU, GPT-3, and LSTM – to their three-component knowledge base, Subject-Predicate-Object (SPO). The highest accuracy was achieved by GPT-3 at 81%, followed by LSTM at 79%.

Table 1 shows the summary of previous studies. Although there are many previous studies related to detecting fake news in texts, there is still a need to propose a methodology to achieve high accuracy for feature extraction and classification by leveraging machine learning and deep learning techniques.

Table 1:

Summary of Previous Studies.

Authors	Dataset	Tweets/Texts	Dataset-split	Methodology	Performance
Anoop, K., Deepak, P., and Lajish, V. (2020) [15]	HWB	1000	…	Naive Bayes	ACC: 79%
				KNN	ACC: 92.5%
				SVM	ACC: 90%
				Random Forests	ACC: 84%
				Decision Tree	ACC: 94%
				AdaBoost	ACC: 96.5%
				CNN	ACC: 91%
				LSTM	ACC: 92%
Sharma, Uma & Saran, Sidarth & Patil, Shankar.. (2020) [16]	LIAR	10240	Training : 67%, Testing: 33%	TF-IDF, Naïve Bayes	ACC: 60%, F1-Score: 72%
				TF-IDF, Random Forest	ACC: 59%, F1-Score:67%
				TF-IDF, Logistic Regression	ACC: 65%, F1-Score: 75%
	REAL-OR-FAKE.CSV	1267		Passive Aggressive	ACC: 92.7%, F1-Score: 92.6%
S. H. Kong, L. M. Tan, K. H. Gan and N. H. Samsudin. (2020) [17]	Two datasets from Kaggle	9805	Training : 80%, Testing: 20%	N-gram, NN of news title	ACC: 77.3%, Recall: 89.7%
				N-gram, NN of news content	ACC: 90.3%, Recall: 97.5%
				TF-IDF, NN of news title	ACC: 74.8%, Recall: 89.8%
				TF-IDF, NN of news content	ACC: 90%, Recall: 94%
J. Shaikh and R. Patil. (2020) [18]	…	6335.4	Training : 80%, Testing: 20%	TF-IDF, and Naïve Bayes	ACC: 84.06%, F1-Score: 81.67%

Authors	Dataset	Tweets/Texts	Dataset-split	Methodology	Performance
				TF-IDF, and SVM	ACC: 95.05%, F1-Score: 93.14%
				TF-IDF, and Passive Aggressive	ACC:92.9%, F1-Score: 92.80%
Iftikhar Ahmad, Muhammad Yousaf, Suhail Yousaf, Muhammad Ovais Ahmad. (2020) [19]	ISOT Fake News	44898	Training: 70%, Testing: 30%	LIWC, Logistic Regression	ACC:97%, F1-Score: 98%
				LIWC, Linear SVM	ACC:98%, F1-Score: 98%
				LIWC, A multilayer perceptron	ACC:98%, F1-Score: 98%
				LIWC, KNN	ACC:88%, F1-Score: 89%
				LIWC, Random Forest	ACC:99%, F1-Score:99%
				LIWC, Voting (RF, LR, KNN)	ACC:97%, F1-Score: 97%
				LIWC, Voting (RF, LSVM, CART)	ACC:96%, F1-Score: 96%
				LIWC, Bagging (Decision Trees)	ACC:98%, F1-Score: 98%
				LIWC, Bossting (AdaBoost)	ACC:98%, F1-Score: 98%
				LIWC, Boosting (XGBoost)	ACC:98%, F1-Score: 99%
				Perez-LSVM	ACC:99%, F1-Score: 99%
				Wang-CNN	ACC:87%, F1-Score: 87%

Authors	Dataset	Tweets/Texts	Dataset-split	Methodology	Performance
				Wang-BiLSTM	ACC:87%, F1-Score: 84%
	From Kaggle	25512		LIWC, Logistic Regression	ACC:91%, F1-Score: 91%
				LIWC, Linear SVM	ACC:37%, F1-Score: 32%
				LIWC, A multilayer perceptron	ACC:35%, F1-Score: 34%
				LIWC, KNN	ACC:28%, F1-Score: 23%
				LIWC, Random Forest	ACC:35%, F1-Score: 32%
				LIWC, Voting (RF, LR, KNN)	ACC:88%, F1-Score: 88%
				LIWC, Voting (RF, LSVM, CART)	ACC:86%, F1-Score: 86%
				LIWC, Bagging (Decision Trees)	ACC:94%, F1-Score: 94%
				LIWC, Boosting (AdaBoost)	ACC:92%, F1-Score: 92%
				LIWC, Boosting (XGBoost)	ACC:94%, F1-Score: 94%
				Perez-LSVM	ACC:79%, F1-Score: 80%
				Wang-CNN	ACC:66%, F1-Score: 67%
				Wang-BiLSTM	ACC:52%, F1-Score: 44%

Authors	Dataset	Tweets/Texts	Dataset-split	Methodology	Performance
	From kaggle	3352		LIWC, Logistic Regression	ACC:91%, F1-Score: 92%
				LIWC, Linear SVM	ACC:53%, F1-Score: 70%
				LIWC, A multilayer perceptron	ACC:94%, F1-Score: 95%
				LIWC, KNN	ACC:82%, F1-Score: 83%
				LIWC, Random Forest	ACC:95%, F1-Score: 95%
				LIWC, Voting (RF, LR, KNN)	ACC:94%, F1-Score: 94%
				LIWC, Voting (RF, LSVM, CART)	ACC:92%, F1-Score: 92%
				LIWC, Bagging (Decision Trees)	ACC:94%, F1-Score: 94%
				LIWC, Boosting (AdaBoost)	ACC:92%, F1-Score: 92%
				LIWC, Boosting (XGBoost)	ACC:94%, F1-Score: 95%
				Perez-LSVM	ACC:96%, F1-Score: 96%
				Wang-CNN	ACC:58%, F1-Score: 31%
				Wang-BiLSTM	ACC:57%, F1-Score: 35%
	Merge (DS1, DS2, DS3)	73762		LIWC, Logistic Regression	ACC:87%, F1-Score: 87%

Authors	Dataset	Tweets/Texts	Dataset-split	Methodology	Performance
				LIWC, Linear SVM	ACC:86%, F1-Score: 87%
				LIWC, A multilayer perceptron	ACC:90%, F1-Score: 90%
				LIWC, KNN	ACC:77%, F1-Score: 77%
				LIWC, Random Forest	ACC:91%, F1-Score: 91%
				LIWC, Voting (RF, LR, KNN)	ACC:88%, F1-Score: 88%
				LIWC, Voting (RF, LSVM, CART)	ACC:85%, F1-Score: 86%
				LIWC, Bagging (Decision Trees)	ACC:90%, F1-Score: 90%
				LIWC, Boosting (AdaBoost)	ACC:86%, F1-Score: 86%
				LIWC, Boosting (XGBoost)	ACC:89%, F1-Score: 90%
				Perez-LSVM	ACC:90%, F1-Score: 90%
				Wang-CNN	ACC:73%, F1-Score: 73%
				Wang-BiLSTM	ACC:62%, F1-Score: 57%
Patwa, Sharma, Pykl, Guptha, Kumari, Akhtar, Ekbal, Das,	COVID-19	10,700	Trainin: 60%, Validation: 20%, Testing: 20%	TF-IDF, and Logistic Regression	ACC: 91.96%
				TF-IDF, and SVM	ACC: 93.32%
				TF-IDF, and Decision Tree	ACC: 85.37%

Authors	Dataset	Tweets/Texts	Dataset-split	Methodology	Performance
and Chakraborty. (2021) [21]				TF-IDF, and Gradient Boost	ACC: 86.96%
Zhang, Cao, Li, Sheng, Zhong, and Shu. (2021) [22]	RumourEval-19	8,439	Training: 60%, Validation: 20%, Testing: 20%	BiGRU	F1-Score: 34%
				BERT	F1-Score: 34.6%
				NileTMRG	F1-Score: 34.2%
	Weibo-16	1,878,384		BiGRU	F1-Score: 82.6%
				BERT	F1-Score: 86.7%
				HSA-BLSTM	F1-Score: 90.8%
	Weibo-20	1,989,802		BiGRU	F1-Score: 85.5%
				BERT	F1-Score: 91.5%
				HSA-BLSTM	F1-Score: 93.2%
Kaliyar, Goswami, and Narang. (2021) [23]	fake news	20,800	…	GloVe, and FakeBERT model	ACC: 98.90%
				Multinomial Naive Bayes	ACC: 89.97%
Sudhakar, and Kaliyamurthie. (2024) [26]	Covid-19	948,373	…	TF-IDF, and Logistic Regression	ACC: 95%
				TF-IDF, and KNN	ACC: 89.98%
				TF-IDF, and Naive Bayes	ACC: 86.89%
				TF-IDF, and SVM	ACC: 89%
				LSTM	ACC: 54%
Asha, and Meenakowshalya (2024) [27]	Corpus	4,233	Training: 80%, Testing: 20%	N=1, TF, SVM	ACC: 78.68%
				N=1, TF-IDF, LSVM	ACC: 93.44%
				N=1, TF, KNN	ACC: 80.58%
				N=1, TF, LR	ACC: 93.21%

Authors	Dataset	Tweets/Texts	Dataset-split	Methodology	Performance
				N=1, TF-IDF, SGD	ACC: 93.60%
				N=1, TF, DT	ACC: 82.16%
Padalko, Chomko, and Chumachenko. (2024) [24]	WELFake	72,134	Trainin: 80%, Testing: 20%	BiLSTM	ACC: 97.49%, F1-Score: 97.48%
				attention based BiLSTM	ACC: 97.66%, F1-Score: 97.62%
Nair, Pareek, and Bhatt. (2024) [29]	FakeNewsNet, BuzzFeedNews, LIAR16	1627, 12836	Training: 80%, Testing: 20%	BERT	ACC: 61%
				GRU	ACC: 75%
				GPT-3	ACC: 81%
				LSTM	ACC: 79%

Several key research challenges were identified across the studies. First, the absence of uniform criteria, which results in differences in evaluation metrics (accuracy, F1-Score, recall) and inconsistent dataset allocation (80/20, 70/30, 60/20/20), is one of the research gaps and difficulties noted in the studies. Second, the lack of extensive and varied datasets and generalization issues, which occur when models trained in one field (like politics) function poorly in another (like health). Third, data bias, which refers to an imbalance between actual and fake news in datasets and the fact that the majority of studies focus solely on English. Fourth, there are constraints in language processing, with about 91% of research concentrating just on English and no useful models for Arabic and other languages. Finally, there are performance difficulties because deep learning models are hard to apply in real-time on a dynamic site like Twitter and require a lot of training time.

Conclusion

The fight against misinformation in the digital age has witnessed remarkable progress with the use of machine learning, deep learning, and natural language (NLP) techniques, to detect fake news from texts. Studies have demonstrated the effectiveness of using advanced methods in identifying fake news and assessing the reliability of news sources. Deep learning models, particularly BERT and BiLSTM, achieved higher accuracy than machine learning models, reaching 98.90%. The study identifies significant research gaps, especially in the field of non-English language processing, and emphasizes the necessity of creating flexible systems that can keep up with the always changing means of spreading false information. These findings provide a solid basis for future research to create more thorough and efficient solutions.

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