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Review Article

Machine Learning Approaches for Fake News Detection on Social Media: A Review

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Abstract

The way people consume news via social media has significant effects on individuals, communities, and organizations. This impacts various areas, including reputation, beliefs, crime rates, and both mental and physical well-being. With these extensive implications, it's crucial to delve into the influence of fake news on social media platforms. Researchers have been investigating the challenges and key findings surrounding fake news detection. This paper aims to lay the groundwork for future studies and organizational initiatives that critically assess the ramifications of misinformation within communities. Several Strategies have been suggested to identify and reduce the spread of fake news online. Research indicates that multimodal approaches those that incorporate various types of data tend to be more effective than methods relying on a single type of data for detecting misinformation.

Additionally, including contextual information has proven to enhance the accuracy of systems designed to detect fake news. Scholars are focusing on pinpointing credible statements and examining user interactions to boost the detection of false information. A vital area of research is understanding how fake news circulates through social networks, as well as the connections among those spreading it. By looking into different forms of news, researchers seek to overcome the limitations of current models to create a more effective automated system for identifying fake news. This review serves as a basis for developing improved, more efficient automated systems for spotting misinformation.

Keywords: Fake news detection, online social media (OSM), Naïve Bayes (NB), Logistic Regression (LR), Multimodality, Contextual information.

1. Introduction

The rapid advancement of technology and the widespread accessibility of the internet have significantly transformed the digital landscape and the way information is disseminated. Social media remains the primary reason for internet usage, with platforms such as WhatsApp, Facebook, Twitter, Instagram, and YouTube gaining immense popularity due to their affordability, ease of use, and viral nature. The number of internet users has surged, engaging with these platforms for various purposes. The digital world is evolving rapidly, with online social media (OSM) surpassing traditional sources as the dominant medium for news consumption. Print media, such as newspapers, are gradually being replaced by online news sources, as the internet provides an abundance of information, largely driven by the increasing popularity of OSM. However, the widespread use of social media, combined with the lack of a requirement for computer literacy, has created opportunities for cybercrimes, particularly through the spread of unverified information. News travels quickly, whether accurate or misleading, and distinguishing between real and fake news is often challenging for users. Misinformation spreads rapidly, both through word of mouth and social media platforms. Fake news refers to deliberately fabricated information designed to deceive the public, often causing reputational harm to individuals, communities, or institutions. It gained widespread attention during the 2016 U.S. presidential elections when false reports fevering one candidate were shared over 37 million times on Facebook. Since then, the issue has drawn increasing concern. Detecting fake news is crucial for ensuring that users receive credible information while maintaining a trustworthy news environment. Given the sheer volume of data on social media, manual detection methods are impractical due to constraints like time, cost, and human effort. Therefore, automated fake news detection systems are essential. Artificial Intelligence (AI) has proven highly effective in tackling this challenge. The following section explores existing research in the field of fake news detection and identifies gaps that need to be addressed for developing a fully automated detection mechanism for social media platforms.

2. Literature Survey

Several Numerous strategies have been devised in recent years to identify and mitigate the spread of fake news. This section explores various research efforts focused on detecting misinformation on online social media platforms. A thorough literature survey indicates that initial fake news detection methods relied heavily on machine learning models. Over time, deep learning techniques gained prominence, and currently, pre-trained models and transfer learning approaches are demonstrating significant effectiveness in this domain.

Aldwairi, M. et al. introduced a browser extension that assists users in filtering out potential clickbait and unreliable websites containing misleading content. Fake news often manipulates multiple modalities, including text, images, videos, and audio, necessitating multi-modal detection frameworks [2].

Yaqing Wang et al. proposed the Event Adversarial Neural Network (EANN), a model designed for real-time fake news detection by learning event-invariant characteristics. Unlike traditional models that struggle with newly emerging and time-sensitive events due to their reliance on event-specific features, EANN effectively generalizes across different contexts. This framework comprises three components: the event discriminator, a multi-modal feature extractor, and a fake news detector. Evaluations conducted on datasets from platforms like Weibo and Twitter demonstrated that EANN outperformed existing baseline techniques by leveraging transferable feature representations [3].

Khan, J. Y. et al. performed an empirical analysis to assess the efficiency of multiple machine learning algorithms on large-scale datasets. Their study categorized 19 models into three groups: standard machine learning models, traditional deep learning approaches, and advanced pre-trained language models such as BERT. Findings indicated that BERT-based systems surpassed other models in both performance and adaptability, even when trained on smaller sample sizes. Additionally, Naive Bayes with N-Gram achieved comparable results to neural networks on large datasets, while LSTM-based models performed best when the input news stories contained substantial information [4].

Gravanis, G. et al. developed a methodology for fake news detection utilizing content-based features and machine learning techniques. This study introduced the "UNBiased" (UNB) dataset, a curated corpus designed for accurate classification tasks. Their model achieved up to 95% accuracy across multiple datasets, with AdaBoost emerging as the top-performing classifier, closely followed by SVM and Bagging techniques [5].

Dhruv Khattar et al. presented the Multimodal Variational Autoencoder (MVAE) for detecting fabricated news. MVAE consists of three main components: a fake news detector, an encoder, and a decoder. By extracting textual and visual features, this model demonstrated superior performance compared to previous multimodal approaches, achieving a 5% improvement in F1-score and a 6% increase in accuracy on datasets from Twitter and Weibo [6].

Abdullah-All-Tanvir et al.proposed an automated approach for classifying news on Twitter, utilizing techniques such as TF-IDF, Count-Vectors, and Word Embedding. Their comparative study of five machine learning models (NB, SVM, LR, and RNN) revealed that SVM achieved the highest accuracy of 74% across different feature sets [7].

Bahad, P. et al. introduced a Bi-Directional LSTM model to detect fake news by analyzing the correlation between news headlines and body text using GloVe embeddings. Their approach outperformed CNNs, vanilla RNNs, and unidirectional LSTMs on high-dimensional datasets [8].

Shu, K. et al. emphasized the importance of user behavior analysis in fake news detection. Their study examined post-sharing patterns and identified key influencers who frequently disseminate misinformation, aiding in the development of more effective detection strategies [9].

Vishwakarma, D. K. et al. developed an image verification framework that cross-checks visual content against web search results. By analyzing the top 15 Google search results, their model assigned a credibility score to images, distinguishing between authentic and manipulated content [10].

Singhal, S. et al. introduced SpotFake, a multi-modal framework that integrates textual and visual analysis. SpotFake employs BERT for textual feature extraction and VGG-19 for image analysis, outperforming existing Twitter and Weibo detection models by 3.27% and 6.83%, respectively [11].

Singhal, S. et al. later refined this model by developing SpotFake+, leveraging transfer learning to improve contextual and semantic understanding. Their study, conducted on the FakeNewsNet repository, marked the first large-scale multimodal analysis on full-length articles and associated images [12].

Kaur, S. et al. designed a multi-level voting mechanism incorporating twelve machine learning classifiers. By leveraging multiple feature extraction techniques, their model achieved higher accuracy compared to individual classifiers. Their findings highlighted Logistic Regression, Passive Aggressive, and Linear SVM as the most effective standalone classifiers, while their ensemble model outperformed them all [13].

Xinyi Zhou et al. developed SAFE, a similarity-aware multi-modal fake news detection system. This model evaluated textual-visual inconsistencies through three modules: multi-modal feature extraction, within-modal fake news prediction, and cross-modal similarity extraction. The results showed that deep learning techniques outperformed traditional machine learning methods in detecting misinformation [14].

Ozbay, F. A. et al. proposed a hybrid approach combining text mining with twenty-three supervised AI algorithms. Evaluations on three real-world datasets confirmed the model's high precision, recall, and F1-score.
(Salazar, A. P. 2020) [16] conducted a comparative analysis of fake news datasets, introducing FakeNewsNet, a comprehensive repository aimed at enhancing misinformation detection efforts [15].

Wang, Y. et al. introduced WeFEND, a weakly supervised learning framework that utilizes user reports to enhance training data. Their model achieved 82.4% accuracy on a large dataset from WeChat [17].

Singhal, S. et al. developed FACTDRIL, a dataset designed for fake news detection in low-resource Indian languages. With over 22,000 samples in eleven languages, FACTDRIL incorporated manual verification strategies to improve the reliability of misinformation classification [18].

Azeri, M. et al. employed machine learning techniques to assess Twitter news credibility. Their study found that

Random Forest achieved the highest accuracy (83.4%) when combining content-based and user-based features [19].

Sahoo, S. R. et al. proposed an automated fake news detection system for Facebook, utilizing deep learning models such as LSTMs, which achieved an accuracy of 99.4% [20].

Collins, B. et al. conducted a survey on misinformation trends and detection methodologies, highlighting the effectiveness of hybrid approaches that combine machine learning, NLP, and fact-checking mechanisms [21].

Kaliyar, R. K. et al. introduced FakeBERT, a deep learning model that integrates BERT with CNNs to enhance natural language comprehension in fake news detection [22].

3. Comparative Analysis

The rise of social media has opened with respect to fake news and its automatic detection. It is an area that affects views and beliefs, business, mental and physical health. Table 1 throws light on the work of eminent researchers in the area of fake news detection using machine learning on social media platforms and a comparative view of the outcome and accuracy observed in each of the work.

Table 1.Comparative Analysis of Fake News Detection

Author Name	**Approach**	**Efficiency/Accuracy (in %)**	**Findings/outcomes**
Y. Wang, fenglong ma et al. 2018 [3]	Their approach centers on Event Adversarial Neural Networks (EANN), which seeks to enhance the accuracy of fake news detection by utilizing multiple types of information, including text, images, and metadata.	71.4% on Twitter dataset and 82.6% on Weibo dataset.	The proposed EANN model surpasses other models in performance and effectively learns transferable feature representations.
J. Y. Khan, M khondaker et al. 2021[4]	Assessment of various machine learning techniques, Utilization of standardized benchmark datasets, Extraction and selection of relevant features, Evaluation using performance metrics, Comparison and analysis of results Emphasis on model generalization.	RoBERTa (Robustly Optimized BERT Approach) attained an accuracy of 96% on the fake vs. real news dataset, 98% on the combined corpus dataset.	Among the 19 models, RoBERTa delivers the best performance on the real vs. fake news dataset and the combined corpus dataset, whereas HAN excels on the LIAR dataset.
Dhruv Khatter et al. 2019[6]	Multimodal Variational AutoEncoder(MVAE)	Achieved 74.4% accuracy on the Twitter dataset and 82.3% on the Weibo dataset.	MVAE surpasses other deep learning models by approximately 6% in accuracy and around 5% in F1-scores.

Abdullah-All-Tanvir et al. 2019[7]	Machine Learning & Deep Learning Approaches: • SVM • NB • LR • RNN • LSTM	SVM-69.47 NB-89.02 LR-89.34 RNN-74 LSTM-78	The results of this study demonstrate that deep learning algorithms outperform traditional machine learning models in detecting fake news, although they demand more computational resources. Additionally, the research highlights the significance of incorporating both text and metadata features to enhance the effectiveness of fake news detection.
Bahad, P. et al. 2019 [8]	Bi-LSTM- RNN (Bi-directional LSTM-recurrent neural network)	----	The outcome of this study emphasizes that the Bi-Directional LSTM model provides a more effective approach for fake news detection, surpassing traditional methods and showcasing its robustness and efficiency in processing textual data.
S. Singhal et al. 2019[11]	Multi-modal framework (SPOTFAKE)	An accuracy of 77.77% was achieved on the Twitter dataset, while the Weibo dataset attained 89.23% accuracy.	The proposed SPOTFAKE system outperforms existing models by approximately 3.27% and 6.83%, respectively.
S. Singhal et al. 2020[12]	SPOTFAKE+	An accuracy of 84.6% was achieved on the fake dataset and 85.6% on the GossipCop dataset from FakeNewsNet.	The proposed SPOTFAKE+ is a multi-modal framework that surpasses other multi-modal frameworks, including EANN, MVAE, and SPOTFAKE.
Xinyi Zhou et al. 2020[14]	Similarity-Aware Multi-Modal FakE news detection system(SAFE)	An accuracy of 87.4% was achieved on the PolitiFact dataset and 83.8% on the GossipCop dataset.	The proposed SAFE system identifies the falsity of news articles by analyzing their text, images, and any inconsistencies between them.
Wang, Y. et al. 2020 [17]	WeFEND (Weakly Supervised Fake News Detection Framework)	An accuracy of 82.4% was achieved on a large collection of news articles from official WeChat accounts.	This model leverages user reports as weak supervision to increase the amount of training data for false news detection. The proposed framework consists of three key components: the annotator, the reinforced selector, and the fake news detector. By integrating these components, the approach enhances both the quantity and quality of training data, adapting to the dynamic nature of news. It achieved an accuracy of 82.4% on a large collection of news articles from official WeChat accounts.

Marina Azer et al. 2021[19]	The approach involves using machine learning algorithms to evaluate the credibility of news on Twitter by analyzing a combination of tweet content, user-related features, and social media interaction.	Logistic Regression (LR) achieves an accuracy of 73.2% using content-based features, while Random Forest (RF) attains 82.2% with user-based features and 83.4% with the overall feature set.	Logistic Regression (LR) performs best with content-based features, whereas Random Forest (RF) excels with user-based features and the overall feature set, which combines both content-based and user-based features. Additionally, user-based features demonstrate better performance compared to content-based features.
S. R. Sahoo et al. 2020[20]	Machine Learning Classifiers: K-NN SVM LR Decision Tree NB Deep Learning Classifier: LSTM	The accuracy obtained using a combination of news content features and user profile features is: KNN- 99.3 SVM- 99.3 LR- 99.0 Decision Tree -99.1 NB- 98.6 LSTM99.4	The deep learning model LSTM outperforms other classifiers, achieving 99.4% accuracy when using a combination of user profile and news content features.
S.Aphiwongsophon et al. 2018[23]	The approach of the article centers on using machine learning models to classify news articles as either real or fake. This is achieved by extracting key textual features, applying data preprocessing techniques, and evaluating different algorithms to determine the most accurate method for detecting fake news.	NB - 96.07 NN - 99.90 SVM- 99.90	SVM and NN perform much better than other methods.
A.Kesarwani et al. 2020[24]	K-Nearest Neighbor (K-NN)	KNN- 79	An accuracy of 79% was achieved when tested on the Facebook news posts dataset.
I. Y. R. Pratiwi et al. 2017[25]	Naïve Bayes (NB)	NB -78.6	A 70:30 ratio of the training and testing dataset yields better performance, achieving an accuracy of 78.6%.
M.Granik et al. 2017[26]	Naïve Bayes(NB)	NB -74	Developed as a software system and evaluated using a dataset of Facebook news posts.

Mrs. Usha. M et al.2023[27]	GRU, LSTM, and RNN	90	The study demonstrates that machine learning techniques, when paired with effective feature extraction and evaluation, can accurately detect fake news. The findings emphasize the potential of machine learning in addressing the spread of misinformation across digital platforms.
Dharmaraj R. Patil, et al. 2022[28]	The approach of the article centers on employing a majority voting technique in conjunction with ensemble learning to enhance fake news detection. By using multiple classifiers, along with feature extraction and data preprocessing, the method improves the system's robustness and accuracy in identifying fake news. like decision tree, logistic regression etc.	96.38%.	The ensemble method significantly enhanced fake news detection accuracy compared to individual classifiers.
Zainab A. Jawad and Ahmed J. Obaid 2022 [29]	The paper explored a hybrid model combining Convolutional Neural Networks (CNN) and Deep Neural Networks (DNN) to analyze textual patterns.	84.6%.	While the model effectively classified news articles, it struggled to differentiate between certain categories, such as "disagree."
Jinyan Su, Claire Cardie, et.al 2023[30]	The study assessed the ability of fake news detection models trained on both human-written and AI-generated news.	---	Models trained exclusively on human-generated content were effective at detecting machine-generated fake news, but the reverse was not true. The study emphasized the importance of a balanced dataset.
Jasraj Singh, Fang Liu, Hong Xu, Bee Chin Ng, & Wei Zhang 2024[31]	The researchers integrated linguistic features into machine learning models to improve detection accuracy.	98.2%	The inclusion of linguistic insights enhanced both performance and interpretability of the models.
Biplob Kumar Sutradhar, Md. Zonaid, Nushrat Jahan Ria, & Sheak Rashed Haider Noori 2023[32]	The study applied machine learning techniques, including Stochastic Gradient Descent, Naïve Bayes, and Logistic Regression, using a dataset of 1,876 news articles. (Naïve Bayes classifier)	56%	The results indicated that higher accuracy could be achieved with more robust models and larger datasets.

S. Pandey, S. Prabhakaran, N. V. Subba Reddy, et al. 2022[33]	The article utilizes various machine learning classifiers and feature extraction methods to identify fake news in online media. It evaluates multiple models, preprocesses the data, and combines different approaches to enhance detection accuracy and performance.	90.46%	Logistic Regression and Support Vector Machine (SVM) were found to be the most effective techniques for this task
Maya Hisham, Raza Hasan, & Saqib Hussain[34]	This study used Support Vector Machine (SVM) with TF-IDF feature extraction to classify fake news.	99.36%	SVM outperformed other classifiers, including Random Forest and Naïve Bayes, in detecting fake news.
S. Bussa, A. Bodhankar, Vinod H. Patil, et al.2023[35]	The researchers implemented Long Short-Term Memory (LSTM) and Support Vector Machine (SVM) models for fake news detection.	LSTM - 94% SVM - 89%	The LSTM model outperformed SVM by effectively capturing long-term dependencies in text.

4. Research Gap

The Extensive research has identified gaps that need to be addressed for developing a more effective and efficient fake news detection system. The section outlines the challenges and areas for improvement in automated fake news detection.

Research Gaps:

1. A single-modality feature poses a challenge in effectively identifying fake news.
2. Several effective methods have been developed using a linguistic approach for fake news detection. However, minimal research has been conducted on visual-based verification.
3. Source verification is a crucial missing component in existing models.
4. The limited dataset size has been identified as a constraint in the current literature.
5. Existing approaches have not given sufficient attention to newly emerging and time-sensitive events.
6. Most researchers have primarily focused on specific types of news, such as political news, leading to dataset bias

This presents an opportunity to leverage a comprehensive dataset with multimodal features for a more effective and efficient automatic fake news detection system. The following challenges need to be addressed for maximizing the system's potential:

1. Since non-manipulated images are mixed with fake news content, distinguishing between real and fake becomes challenging
2. The lack of editorial rigor further complicates the identification of fake news.
3. A well-structured dataset containing contextual information and a complete multimodal collection of fake news data types is necessary.
4. Verifying sources and assessing author credibility remains a challenge for researchers
5. Currently, there are no efficient mechanisms in place to identify and limit the spread of fake news on social media.
6. Incorporating contextual information is essential to enhance the model's efficiency.
7. Extracting explainable check-worthy phrases, user comments, fake news dissemination patterns, and connections between spreaders can be valuable in distinguishing fake from real news

Analyzing the connection between the news title and body text, as well as the correlation across different modalities, can help improve accuracy and efficiency.

5 Conclusions

A thorough and critical evaluation provides comprehensive research insights for detecting fake news while addressing its impact on individuals, society, and organizations. With the vast amount of information available, social media has become a primary platform for online content consumption. However, manually classifying news articles is impractical due to the significant manpower, cost, time, and expertise required. Consequently, automated fake news detection is essential. Research indicates that in both single-modality (text-only) and multi-modality approaches, the primary focus is on feature extraction techniques involving text and images. Textual feature extraction is performed using methods such as Text-Convolutional Neural Network (Text-CNN), Term Frequency-Inverse Document Frequency (TF-IDF), Hashing-Vectorizer (HV), and Count-Vectorizer (CV). Meanwhile, visual feature extraction is carried out using VGG-19.

Various Machine Learning, Deep Learning, Transfer Learning, and Pre-trained models have been analyzed to gain a deeper understanding of previously implemented fake news detection approaches. Findings suggest that pre-trained and deep learning models exhibit the highest effectiveness in identifying fake news.

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