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"Advancements in Fake News Detection: A Comparative Study of Machine and Deep Learning Methods"

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Abstract
In the contemporary landscape of information dissemination, the detection of fake news has emerged as a crucial undertaking due to the rapid proliferation of misinformation across various online channels. This study undertakes a comprehensive examination of fake news detection techniques, encompassing both traditional machine learning and advanced deep learning methods. We explore the efficacy of diverse feature extraction methods coupled with supervised learning methods. Through experiments conducted on established benchmark datasets, we assess the performance of these approaches in terms of classification report, while also scrutinizing their computational efficiency and scalability. Our findings offer valuable insights into the strengths and limitations of each method for fake news detection, thereby furnishing researchers and practitioners with guidance for formulating effective strategies to combat misinformation across online media platforms.

Keywords: Fake News; Machine Learning; Deep Learning;

I. INTRODUCTION

Fake news denotes deceptive or inaccurate information masquerading as authentic news. It may be deliberately fabricated to mislead audiences or inadvertently disseminated due to misinformation or misinterpretation. The dissemination of fake news frequently serves to sway public opinion, advance specific agendas, or increase interaction and viewership on social media channels.

Detecting fake news is important for several reasons:

- **Preserving Truth:** Fake news undermines the truth and can lead to widespread misinformation. It's crucial to distinguish between fact and fiction to maintain an informed society.
- **Protecting Public Discourse:** False information can distort public discourse, leading to misguided beliefs, decisions, and actions. Detecting fake news helps prevent these negative consequences.
- **Safeguarding Democracy:** In democratic societies, an informed electorate is essential. Fake news can manipulate public opinion and influence elections, threatening the integrity of democratic processes.
- **Preventing Harm:** Fake news can incite fear, hatred, and violence. By detecting and debunking false information, we can mitigate the potential harm it may cause to individuals and communities.
- **Promoting Media Literacy:** Teaching people how to identify and evaluate fake news promotes media literacy skills, empowering individuals to critically assess information and make informed decisions.

Overall, detecting fake news is vital for upholding truth, fostering informed public discourse, safeguarding democracy, preventing harm, and promoting media literacy.
Several strategies for detecting misinformation abound, encompassing fact-checking by esteemed entities, assessing source credibility, cross-referencing information from diverse sources, and employing computational tools like natural language processing and machine learning to pinpoint deceptive patterns. Tackling fake news necessitates a comprehensive approach, involving initiatives such as educating on media literacy, fostering critical thinking, enhancing methods for detection and flagging, and fostering collaboration among tech firms, policymakers, journalists, and civil society groups.
This paper assesses the efficacy of various learning methods across diverse datasets and tasks, providing insights into their strengths, weaknesses, and suitability. Our study

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meticulously scrutinizes learning methods to determine the most effective for handling extensive datasets.

II. LITERATURE REVIEW

The rise of fake news in the digital era has underscored the need for advanced tools and methodologies to detect and categorize it. Conventional techniques like manual fact-checking and keyword-based methods have shown limitations in addressing the vast quantity and intricate nature of fake news present on the internet [1] (Cano-Marin et al., 2023).

In their 2022 research, Dutta et al. [2] present a hybrid deep learning classification model aimed at identifying and categorizing fake news and misleading content within the "COVID-19 Fake News Dataset" sourced from Mendeley, consisting of articles and web content related to COVID-19. Their model achieved an accuracy of 75.34%, outperforming existing LSTM and BiLSTM techniques. This highlights the effectiveness of their model in autonomously and accurately distinguishing between genuine and false information surrounding the COVID-19 pandemic.

Various approaches have been explored for detecting fake news, as evidenced by research conducted by Ahmed et al. [3], which utilizes N-gram and TF–IDF methods for feature extraction, along with classifiers such as Stochastic Gradient Descent (SGD), Support Vector Machine (SVM), Linear Support Vector Machine (Linear SVM), K-Nearest Neighbor (KNN), and Decision Tree (DT). Using the ISOT Fake News dataset, Ahmed et al. achieved an accuracy of 92% employing the Linear SVM classifier. In contrast, Ozbay and Alatas [4] employed TF–IDF exclusively for feature extraction, albeit with a broader array of classifiers including ZeroR, CV Parameter Selection (CVPS), Weighted Instances Handler Wrapper (WIHW), and DT, among others. Their approach surpassed the results reported in [5], achieving an accuracy of 96.8% along with high precision, recall, and F1-scores.

Ahmad et al. [5] conducted similar research to [3], [5], comparing individual learning algorithms with ensemble learning algorithms. They evaluated Logistic Regression (LR), LSVM, Multilayer Perceptron (MLP), and KNN individually, then compared them with ensemble learning methods such as Random Forest (RF), Voting Classifier, Bagging Classifier, and Boosting Classifier across multiple datasets. Results from testing on the first dataset outperformed those in [4], with the RF algorithm achieving accuracy, precision, recall, and F1-scores of 99%, 99%, 100%, and 99%, respectively. The RF algorithm also performed well on the third and fourth datasets, with accuracies of 95% and 91%, respectively.

In contrast, Kaliyar et al. [6] proposed a distinct approach to fake news detection, opting for a pre-trained word embedding (Glove) combined with a Convolutional Neural Network (CNN), rather than TF–IDF and traditional machine learning algorithms. Using the Fake News Dataset [4], their method surpassed Ahmad et al.'s study [3], achieving higher accuracy, precision, recall, and F1-score.

Bahad et al. [7] also investigated fake news detection using the Fake News Detection Dataset [5], employing GloVe pre-trained word embeddings combined with various deep learning architectures including CNN, Recurrent Neural Network (RNN), Unidirectional Long Short-Term Memory (LSTM), and Bidirectional LSTM. Results varied, with one architecture outperforming Ahmad et al.'s [3] study with 98.75% accuracy using Bidirectional LSTM. Additionally, Bahad et al. tested the Fake or Real News Dataset [8], achieving 91.48% accuracy using Unidirectional LSTM.

Hadeer Ahmed et al. [8] devised a fake news detection model that integrated machine learning methods alongside n-gram analysis. Their study entailed thorough exploration and comparison of two distinct feature extraction techniques and six machine learning classification techniques. The experimental assessments revealed that the most optimal combination involved utilizing TF-IDF for feature extraction paired with LSVM as the classifier. This particular approach yielded an impressive accuracy rate of 92%.

Uma Sharma et al. [9] introduced an approach to identify counterfeit news utilizing machine learning algorithms. Their method comprises feature extraction, data preprocessing, and classification employing a range of machine learning algorithms. The researchers observed that the SVM classifier achieved an accuracy of 94.5%.

[10] Abdulrahman and Baykara (2020) focus on classifying fake news on social media, primarily examining textual content due to the increasing prevalence of fake news on these platforms. They employ four feature extraction methods and ten classifiers, finding that convolutional neural networks are particularly effective, achieving accuracy rates ranging from 81% to 100%. This highlights the effectiveness of their approach for fake news classification. [11] Various deep learning architectures like CNNs, RNNs, and LSTMs have been studied for fake news classification. Recent advancements, such as attention-based mechanisms, have improved model performance by highlighting relevant text parts (Islam et al., 2020). These developments have significantly advanced efforts to combat fake news, leading to more accurate and efficient classification models.

Syed et al. (2023) propose a hybrid approach combining weakly supervised learning, deep learning, and feature extraction techniques to tackle fake news detection in unlabeled social media data. Their method employs Bi-GRU and BiLSTM deep learning models alongside TF-IDF and Count Vectorizers for feature extraction. Results show 90% accuracy in fake news detection, highlighting the effectiveness of their approach, especially in data lacking labels [12].

III. METHODOLOGY

The dataset provided on Kaggle, tailored specifically for fake news detection, serves as a valuable resource for identifying and combating misinformation. It comprises an extensive collection of news articles, each meticulously labeled to denote its authenticity. By leveraging this dataset, learning models can be trained to discern intricate patterns within the textual data and accurately predict the credibility of news articles. Sourced from reputable news outlets such as Politico, NPR, CNN, and Reuters, the dataset is curated with utmost

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care to ensure its reliability and accuracy. Furthermore, it encompasses a diverse range of news articles spanning various categories including politics, business, entertainment, and more, thereby offering a comprehensive representation of real-world scenarios. In the subsequent sections, we provide a detailed methodology outlining the implementation of various feature extraction techniques and model training methods to maximize the effectiveness of fake news detection.

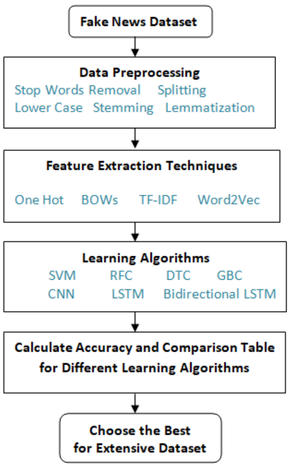

Figure 1: Steps for implementing different learning methods

A. DATASET

The dataset named "train.csv," accessible on Kaggle, is commonly utilized in distinguishing between authentic and deceptive news articles. It consists of a compilation of news pieces accompanied by corresponding labels indicating their authenticity. By utilizing this dataset, machine learning methods can be trained to recognize patterns within the textual content, facilitating predictions regarding the truthfulness of news articles.

Dataset Description:
train.csv: This dataset serves as a comprehensive training set and includes the following attributes:
id: A unique identifier for each news article.
title: The title of the news article.
author: The author of the news article.
text: The textual content of the article, which may be incomplete.
label: A label categorizing the article as potentially unreliable.
1: Indicates an unreliable article.
0: Denotes a reliable article.

B. PRE-PROCESSING

During the preprocessing phase of a fake news dataset, essential libraries such as PorterStemmer and stopwords from the NLTK (Natural Language Toolkit) are imported in Python. Furthermore, regular expressions are employed to effectively manage and filter the textual content.

Here's a concise overview of the preprocessing steps:
Importing Libraries: Commence by importing the required libraries such as PorterStemmer and stopwords from NLTK. These libraries offer functionalities for stemming and eliminating common words (stopwords) that may not significantly contribute to the analysis.

Additionally, here are some new data entries:

- **Tokenization:** Utilize tokenization techniques to split the text into individual words or tokens, enabling further analysis at the word level.
- **Lowercasing:** Convert all text to lowercase to ensure consistency and facilitate comparison between words.
- **Removing Punctuation:** Eliminate punctuation marks from the text, as they may not carry meaningful information for analysis.
- **Removing HTML Tags:** If the text contains HTML tags, remove them to extract only the relevant textual content.
- **Normalization:** Finally, consider additional normalization techniques such as converting all text to lowercase to ensure consistency in the dataset.

These preprocessing steps are crucial for cleaning and preparing the dataset before applying machine learning or deep learning models for fake news detection.

C. FEATURE EXTRACTION TECHNIQUES

Feature extraction techniques are essential in natural language processing, especially for fake news detection. They convert raw text data into numerical representations suitable for machine learning algorithms. Methods like One Hot Encoding, Bag of Words (BoW), Term Frequency-Inverse Document Frequency (TF-IDF), and Word2Vec are commonly used. Feature extraction includes strategies such as n-grams, word embeddings, topic modeling, and syntactic or semantic analysis, chosen based on data complexity, desired representation level, and available computational resources.

In fake news detection, popular techniques include:

- **Bag of Words (BoW):** Treats documents as collections of words, disregarding grammar and order. It builds a vocabulary of unique words and counts their occurrences in each document, useful for word presence detection but lacking in context awareness.
- **Term Frequency-Inverse Document Frequency (TF-IDF):** Evaluates word importance relative to a document collection, assigning higher scores to words frequent in a document but rare across all documents. It helps identify unique and significant words in specific documents.
- **Word Embeddings:** Represent words as dense vectors in a continuous space, capturing semantic relationships. Methods like Word2Vec, GloVe, and FastText learn word vector representations from context, preserving semantic similarities and improving understanding of word meaning and context in fake news articles.

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By leveraging these techniques, machine learning models can identify patterns and connections in text data, enhancing fake news detection accuracy. However, each method has its strengths and weaknesses, requiring careful consideration based on dataset characteristics and detection objectives.

D. LEARNING METHODS

We are using different learning methods to find the accuracy of the model:

(i) Support Vector Machine

Support Vector Machine (SVM) is a supervised learning algorithm employed for classification and regression duties. Its chief goal is to locate the optimal hyperplane that distinctly segregates various classes within the feature space. SVMs boast several advantages, such as their adeptness in high-dimensional spaces, capability to address non-linear data using the kernel trick, and resilience to overfitting by maximizing the margin. Nonetheless, they can be responsive to kernel and parameter selections, and they may exhibit subpar performance with extensive datasets due to their computational complexity.

(ii) Random Forest Classifier

Random Forest is a popular ensemble learning algorithm used for classification and regression tasks. It mitigates overfitting through its ensemble approach and handles missing values well. Additionally, it provides valuable insights into feature importance. Notably, training a Random Forest can be computationally intensive, particularly when dealing with large datasets containing numerous trees and features. However, training can be computationally intensive, and interpreting individual trees within the ensemble may pose challenges compared to simpler models.

(iii) Decision Tree Classifier

A Decision Tree Classifier is a supervised learning algorithm primarily used for classification tasks, dividing the feature space into subsets based on feature values.

These classifiers offer interpretability, as they are easy to understand and visually represent. They require minimal data preprocessing and can handle both numerical and categorical data without normalization. Decision Trees can capture nonlinear relationships effectively, providing flexibility in modeling complex datasets.

However, they are prone to overfitting, especially with deep trees or noisy datasets, which affects generalization. Additionally, they exhibit high variance, resulting in different trees for different training subsets, impacting stability. Small fluctuations in the data may *result in entirely different tree structures, rendering Decision Trees unstable* in certain scenarios.

(iv) Gradient Boosting Classifier

the Gradient Boosting Classifier is an ensemble learning method utilized for classification tasks, sequentially building weak learners (typically decision trees) to correct errors made by preceding models.

This technique offers several strengths in machine learning. It excels in predictive accuracy by leveraging the collective strengths of multiple weak learners, handling diverse data types without extensive preprocessing, and demonstrating robustness to overfitting through its sequential fitting approach. However, *training can be computationally expensive, especially for large datasets* and complex models, and requires careful tuning of hyperparameters for optimal performance. Despite its resistance to overfitting, regularization techniques may be necessary to prevent it, such as early stopping and tree pruning.

(v) Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are deep learning models primarily used for image-related tasks like classification, detection, and segmentation. They automatically learn hierarchical features from input images through convolutional filters. CNNs excel in hierarchical feature learning, translation invariance, and parameter sharing, making them efficient and effective for computer vision tasks. They have revolutionized the field and are considered the state-of-the-art approach for image-related tasks.

(vi) Long Short-Term Memory

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) structure designed to grasp long-term dependencies in sequential data, such as time series data, text, and audio. It tackles the vanishing gradient issue encountered in traditional RNNs, enabling them to learn and retain information over extended sequences.

LSTM stands out as a potent and adaptable architecture for modeling sequential data, excelling at capturing long-term dependencies and delivering outstanding performance across various applications.

By selectively updating and forgetting information over time, LSTMs demonstrate an ability to effectively capture long-range dependencies in sequential data. This characteristic makes them particularly suitable for a variety of tasks, including language modeling, machine translation, speech recognition, and time series prediction.

(vii) Bidirectional LSTM

Bidirectional Long Short-Term Memory (Bi-LSTM) represents an advancement of the conventional LSTM framework, which processes input sequences in both forward and backward directions. This capability permits the model to grasp dependencies from both past and future contexts concurrently, resulting in enhanced comprehension and representation of the input sequence.

Here's how a Bidirectional LSTM works:

- **Forward LSTM:** The input sequence is fed into one LSTM layer in the forward direction, where each input token is processed one at a time from left to right. The LSTM layer maintains hidden states and cell states, updating them at each time step based on the current input token and the previous hidden and cell states.
- **Backward LSTM:** Simultaneously, the same input sequence is fed into another LSTM layer in the backward direction, where each input token is processed one at a time from right to left. Similar to the forward LSTM, the backward LSTM maintains hidden states and cell states, updating them at each time step based on the current input token and the previous hidden and cell states.

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- **Concatenation:** After both the forward and backward LSTMs have processed the entire input sequence, the outputs from each LSTM layer are concatenated together. This results in a final output sequence where each token representation contains information from both past and future contexts.
- **Final Output:** The combined output sequence is subsequently forwarded to subsequent layers within the neural network for additional processing or prediction. In classification scenarios, a typical approach involves applying a softmax layer atop the concatenated outputs to generate class probabilities.

By analyzing input sequences bidirectionally, Bi-LSTMs efficiently capture extensive dependencies and contextual details from both past and future contexts. This feature renders them especially valuable for tasks that necessitate a comprehensive grasp of the entire input sequence, such as natural language processing (NLP), speech recognition, and sequence labeling.

IV. RESULTS AND DISCUSSION

Here, we are using various learning methods with feature extraction techniques to detect the fake news. In our analysis, SVM demonstrates moderate effectiveness in detecting fake news. While it achieves decent accuracy, its performance may be limited by its inability to capture complex patterns effectively. Random Forest ensemble approach allows it to capture diverse feature interactions and handle noisy data efficiently, leading to competitive accuracy. Moreover, Random Forest's ability to highlight feature importance aids in identifying critical indicators of fake news. Decision Tree models simplicity and interpretability exhibit limitations in effectively distinguishing fake news. High variance and susceptibility to overfitting, especially with complex datasets, hinder their performance. While Decision Trees offer insights into decision-making processes, their capacity to discern nuanced relationships may constrain their effectiveness. Gradient Boosting outperforms other machine learning models in fake news detection. By iteratively refining model predictions and minimizing errors, Gradient Boosting effectively discriminates between fake and genuine news articles.
For large datasets, deep learning models, particularly those based on neural networks, tend to perform well. Specifically, learning models can handle large amounts of data effectively.

These models can learn complex patterns and representations from vast amounts of text data, making them well-suited for tasks like fake news detection. Additionally, deep learning models can take advantage of parallel processing capabilities, which accelerates training on large datasets compared to traditional machine learning methods. However, it's important to consider computational resources when working with large datasets and deep learning models, as training these models can be resource-intensive. Distributed computing frameworks like TensorFlow or PyTorch can help leverage parallel processing across multiple GPUs or even distributed clusters to train models more efficiently on large datasets.

Table 1: Comparison Table of Learning Methods

S. No.	Learning Methods	Accuracy	
		Small Dataset	Large Dataset
1.	Support Vector Machine	0.92	0.86
2.	Random Forest Classifier	0.93	0.85
3.	Decision Tree Classifier	0.94	0.87
4.	Gradient Boosting Classifier	0.93	0.87
5.	Convolutional Neural Network	0.91	0.94
6.	Long Short-Term Memory	0.93	0.96
7.	Bidirectional Long Short-Term Memory	0.96	0.99

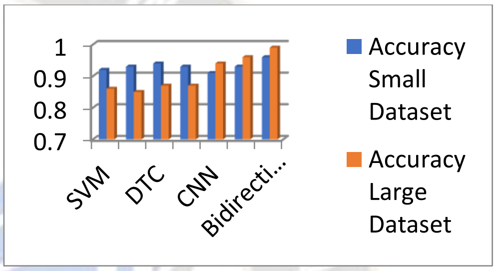

Figure 2: Comparison Chart for different Learning Methods (Accuracy)

CNNs, known for their hierarchical feature learning capabilities, may face challenges in fake news detection due to the sequential nature of text data. While CNNs excel in tasks like image classification, their performance in capturing the subtleties of fake news may be limited by the inherent limitations of convolutional filters in text analysis. Our analysis suggests that LSTMs and Bidirectional LSTMs hold promise for detecting fake news by capturing long-range dependencies in sequential data. These models leverage bidirectional processing to incorporate both past and future contexts, potentially improving their ability to discern fake news articles.

Bidirectional LSTM

accuracy_score (y_test, y_pred1): 0.96
Creating classification report: print (classification_report (y_test, y_pred1))

Table 2: Classification Report (Small Dataset)

	Precision	recall	f1-score	support
0	0.96	0.97	0.97	3419
1	0.94	0.95	0.95	2616
accuracy	--	--	0.96	6035
macro average	0.96	0.96	0.96	6035
weighted average	0.96	0.96	0.96	6035

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accuracy_score (y_test, y_pred1): 0.99
Creating classification report: print (classification_report (y_test, y_pred1))

Table 3: Classification Report (Large Dataset)

	precision	recall	f1-score	support
0 (reliable)	0.99	0.99	0.99	7777
1(unreliable)	0.99	0.99	0.99	7037
accuracy	--	--	0.99	14814
macro average	0.99	0.99	0.99	14814
weighted average	0.99	0.99	0.99	14814

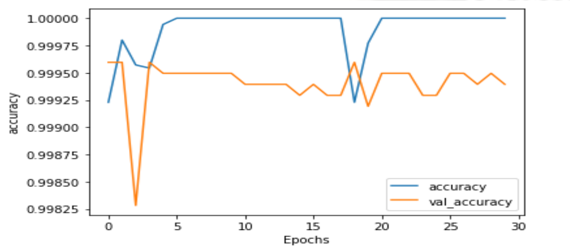

Figure 3: Accuracy Report for Bidirectional LSTM

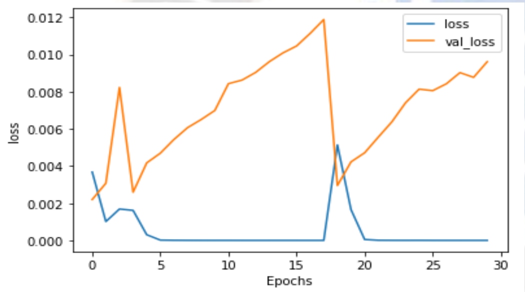

Figure 4: Loss Report for Bidirectional LSTMV.

CONCLUSION AND FUTURE WORK

Our comparative analysis underscores the pivotal role of model selection in determining the efficacy of fake news detection systems. We observed that machine learning methods exhibit robust performance in discerning fake news from genuine content. These models leverage various techniques to effectively capture patterns and relationships within the data, leading to accurate classification outcomes. However, deep learning methods show promise for enhancing fake news detection by leveraging their ability to process sequential data and capture intricate patterns over long ranges. These models excel in learning hierarchical representations of features and can potentially uncover subtle nuances indicative of fake news articles. Bidirectional LSTM becomes the best model which works on large dataset and gives high accuracy to detect fake news.

Moving forward, future research endeavors should prioritize refining the architectures of these models to further improve their performance in fake news detection tasks. Additionally, exploring ensemble approaches, which combine multiple models to leverage their complementary strengths, could enhance the robustness and reliability of fake news detection systems. Moreover, integrating external features such as metadata, user behavior, and social network dynamics could provide valuable context and enhance the generalization capabilities of these systems. By continually advancing model development and incorporating innovative methodologies, we can bolster the effectiveness and reliability of fake news detection.

CONFLICT OF INTEREST

Authors declare no conflict of interest exists.

REFERENCES

1. Cano-Marin, E., Mora-Cantallops, M., and Sanchez-Alonso, S. (2023). The power of big data analytics over fake news: a scientometric review of Twitter as a predictive system in healthcare. Technol. Forecast. Soc. Change 190, 122386. doi: 10.1016/j.techfore. 2023.122386
2. Dutta, R., Ranjan, D., and Majumder, M. A. (2022). Deep learning model for classification of COVID-19 related fake news. Lect. Not. Electr. Eng. 860, 449–456. doi: 10.1007/978-981-16-9488-2_42
3. Ahmed H., Traore I., Saad S. Detection of Online Fake News using N-Gram Analysis and Machine Learning Techniques, Lect. Notes Comput. Sci. (Including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics) (2017), pp. 127-138, https://doi.org/10.1007/978-3-319-69155-8_9
4. Ozbay F.A., Alatas B. Fake news detection within online social media using supervised artificial intelligence algorithms Phys. A Stat. Mech. Appl., 540 (2020), Article 123174, https://doi.org/10.1016/ j.physa.2019.123174
5. Ahmad I., Yousaf M., Yousaf S., Ahmad M.O. Fake news detection using machine learning ensemble methods Complexity, 2020 (2020), pp. 1-11, https://doi.org/10.1155/2020/8885861
6. Kaliyar R.K., Goswami A., Narang P., Sinha S. FNDNet – A deep convolutional neural network for fake news detection Cogn. Syst. Res., 61 (2020), pp. 32-44, https://doi.org/10.1016/j.cogsys.2019.12.005
7. Bahad P., Saxena P., Kamal R. Fake news detection using bi-directional LSTM-recurrent neural network Procedia Comput. Sci., 165 (2019), pp. 74-82, https://doi.org/10.1016/j.procs.2020.01.072
8. Issa Traore, Hadeer Ahmed and Sherif Saad, "Detection of Online Fake News Using N-Gram Analysis and Machine Learning Techniques" International Conference on Intelligent, Secure, and Dependable Systems in Distributed and Cloud Environments.
9. Sidarth Saran, Uma Sharma, and Shankar M. Patil. "Fake News Detection Using Machine Learning Algorithms".International Journal of creative research thoughts(IJCRT) 2020.
10. Abdulrahman, A., and Baykara, M. (2020). Fake news detection using machine learning and deep learning algorithms. 3rd Int. Conf. Adv. Sci. Eng. 5, 18–23. doi: 10.1109/ICOASE51841.2020.9436605
11. Islam, M. R., Liu, S., Wang, X., and Xu, G. (2020). Deep learning for misinformation detection on online social networks: a survey and new perspectives. Soc. Netw. Anal. Min. 10, 696. doi: 10.1007/s13278-020-00696-x
12. Syed, L., Alsaeedi, A., Alhuri, L. A., and Aljohani, H. R. (2023). Hybrid weakly supervised learning with deep learning technique for detection of fake news from cyber propaganda. Array 19, 100309–100309. doi: 10.1016/j.array.2023.100309