Heliyon 10 (2024) e36049

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Fake social media news and distorted campaign detection framework using sentiment analysis & machine learning

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ARTICLE INFO

Keywords:
Sentiment analysis
Social media
Fake news
Distorted campaigns
Bots

ABSTRACT

Social networking platforms have become one of the most engaging portals on the Internet, enabling global users to express views, share news and campaigns, or simply exchange information. Yet there is an increasing number of fake and spam profiles spreading and disseminating fake information. There have been several conscious attempts to determine and distinguish genuine news from fake campaigns, which spread malicious disinformation among social network users. Manual verification of the huge volume of posts and news disseminated via social media is not feasible and humanly impossible. To overcome the issue, this research presents a framework to use sentiment analysis based on emotions to investigate news, posts, and opinions on social media. The proposed model computes the sentiment score of content-based entities to detect fake or spam and detect Bot accounts. The authors also present an investigation of fake news campaigns and their impact using a machine learning algorithm with highly accurate results as compared to other similar methods. The results presented an accuracy of 99.68 %, which is significantly higher as compared to other methodologies delivering lower accuracy.

1. Introduction

Social is the most innovative and disruptive technology of our times. It is highly important for each of us, with its own set of benefits and drawbacks. Since social media and news articles are readily available, inexpensive, and instantaneous, people utilize them as their main sources of news and content. The emergence of false information and news on social platforms is now a significant problem. Instead of traditional sources, the trend of searching for information using social media sources has been on the rise. The advantage is reaching out to a huge number of global viewers quickly, yet it is precisely because of this that social media platforms are the ideal platforms to influence public views and change opinion. During the US presidential election of 2016, fake news and inaccurate stories were widely disseminated, and this trend persisted until the current COVID-19 outbreak in 2021. Social media began to buzz in February 2020 with disturbing photos, videos, and reports about Coronavirus in January 2020, even as WHO [1] had already released a report.

Yet, unreliable news and inaccurate posts started spreading globally, faster than the virus itself. In July 2021, US President Joe Biden hit out against social media platforms [2] alleging, instead of being supportive, that misinformation campaigns and fake posts

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https://doi.org/10.1016/j.heliyon.2024.e36049
Received 1 August 2024; Accepted 8 August 2024
Available online 10 August 2024

around COVID-19 and vaccines on social media platforms were killing people. Fast broadband speeds and the adoption of smartphone apps have led to anytime anywhere access to information and news, unlike traditional print media. As per Pew Research's social media fact sheet (2021) [3], from just 5 % in 2005, in 2021 over 70 % of Americans use social media platforms to interact post views and opinions, and access global news.

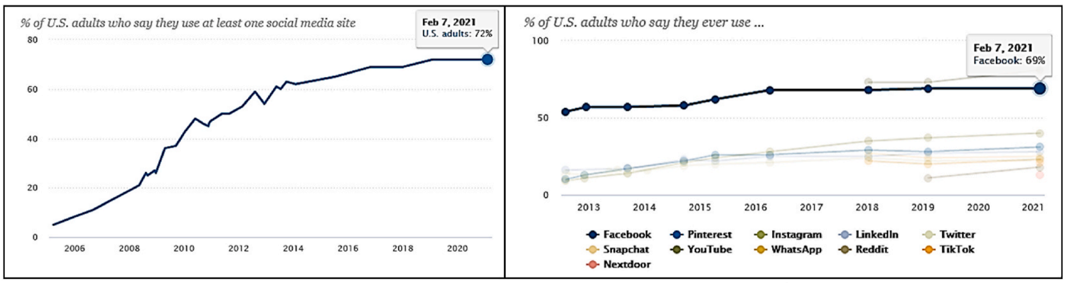
The biggest contributor to the propagation of fake pictures is social media. Fake pictures are photographs that have been altered to modify the information they represent. Fake pictures shared on social media platforms lead to distortion and division among the public. Fake news spread misinformation linked to the pandemic, about COVID-19 being the fake or huge drop in cases, when in fact the second wave was ravaging the world and more specifically the US. Although rumors are dependent on the intent of the source and may not be fake at times, fake news certainly turns out to be fake and is a disinformation campaign. These are propagated by Bots, paid posters, political or activists, terrorists, state-sponsored trolls, media houses, and individuals. The motivations range from monetary benefits, hurt and disrepute, creating disorder, manipulating opinions, or simply promoting individual beliefs. Fake and an over-abundance of misinformation widely spread over social media platforms across the globe. This included Internet search engines Google, Bing, and Yahoo among others, which are powerful sources of gathering information over the web. Fig. 1a has the X-axis representing the adult percentage who use social media sites (at least once) and Fig. 1b presents the X-axis as the percentage of persons no using any social media sites and Y-axis in both presents the year range. Both illustrate the facts about the rise of social media and Facebook, X (now renamed X), LinkedIn, WhatsApp, Instagram, Snapchat, YouTube, TikTok, Pinterest, Tumblr, and Koo as the prime sources for disseminating news and information.

Sentiment-related behavior, expressions, and their analysis are important aspects of detecting such fake campaigns and spam posts. Users tend to comment, like, or forward posts that are aroused when they lack or feel in full control over the posts. Sentiment analysis [4] involves the utilization of natural language process techniques and models to determine the content and the word texts involving subjective or objective posts. This helps determine if the posted expressions are positive, negative, or neutral in weak or strong ways. Since a lot of analysis involves opinions on social media, this is known as Opinion mining [5]. To spread misinformation, fake headlines, and campaigns, utilize emotions, negative/positive polarity, and strong/weak curiosity, simulating to engage and at times use computer apps designed to post automated messages. The commercial and academic realms have focused a great deal of emphasis on the serious problem of false posts and news. Since real or fake posts and campaigns differ so little, identifying fake posts and news is challenging.

The circulation of fake social media news platforms in today's digital world has put public discourse, political campaigns, and societal welfare at risk. The detection and mitigation of fake information presents a lot of challenges, including the spread of such false news, the flexibility with which malevolent actors can maneuver, and the difficulty of telling authentic content from fabricated stories. The present methods for detecting fake news often suffer from scalability, accuracy, and adaptability problems. This necessitates the use of creative solutions that can handle this hectic setting. Because of the following factors, conducting sentiment analysis on news is essential, particularly when considering the research background.

- Understanding Emotional Impact on Public Perception
- Identifying Manipulative Tactics through Emotional Language
- Cultural Nuances and Contextual Relevance
- Enhanced Accuracy in Distinguishing Misinformation
- Real-Time Adaptability to Evolving Emotional Trends
- Addressing Cultural and Linguistic Specificities
- Comprehensive Understanding of News Impact.

Combining sentiment analysis and machine learning approaches, the framework proposed in this research project presents a fresh approach for fake news identification. The approach improves its capacity to detect not only the textual content but also the underlying emotions and subjective tones related with social media articles, posts, and news by including sentiment analysis into the identification process. Thanks to its growing awareness, the suggested model found minute linguistic variations that can point to dishonest behaviour, therefore offering a more complete and contextually aware approach to spot fake news. Moreover, the framework's machine learning elements are made to control the dynamic character of false news strategies by means of adaptive algorithms able to



a b

Fig. 1. a: Use at least one Social Media site Fig. 1b: Not using any Social media [3].

detect and react to fresh patterns of dishonesty.

This study provides a sound and practical framework that adjusts to the subtleties of the contemporary information environment, while also contributing to the theoretical understanding of the challenges in identifying fake news. The proposed methodology dives into sentiment analysis as the step forward in the continuing efforts to detect fake posts and news. The highlights for this research are.

- Focus on fake post and news campaigns detection on social media platforms using sentiment analysis and advanced frameworks and their comparative comparison with existing related techniques.
- Calculates content-based sentiment score to detect fake posts and news campaigns in real-time.
- Designed and implement machine-learning algorithm that can investigate fake news and its impact.
- Achieved accuracy of 99.68 %, which is significantly higher as compared to other methodologies delivering lower accuracy as Kai Shu et al. (2019) [6] (86.4 %), Julio et al.(2019) [7] (85 %), Xinyi et al. (2019) [8] (92.9 %), and Kai Shu et al. (2019) [9] (90.4 %).

This research is segregated into the following sections: After presenting and describing the research problem in the Introduction, Section two discussed related publications by other researchers. Section three describes the dark side of fake news and malicious campaigns in recent times and their impact. Section four describes the research methodology and steps for sentiment analysis and machine learning for detection. Section five presents the research performed using the dataset along with the results obtained after comparing the framework proposed and the existing models. This is followed by the conclusion as well as the future research options and finally the references cited in this research.

2. Literature review

This section presents the previously published research articles and methods for fake news campaigns and spam post-detection on social media platforms. The selection involved a staged process illustrated in Fig. 2.

The authors identified 284 published research works from Springer, IEEE, and other journals during which the authors classified the literature and shortlisted 38 similar works closely matched to this research. The literature papers selected are referenced and presented in Table 1.

Fake News has now become a huge issue that is spreading devastation throughout the globe. The negative consequences include an absence of verification of the source of legitimacy, as well as the veracity of the viewpoints being promoted. To improve accuracy, Bhutani et al. (2019) [10] suggested a method for identifying false news that takes sentiment into account. Using three distinct data sets and various approaches, the authors evaluated and compared the suggested method's performance. The proposed approach outperformed the other techniques, according to the findings.

Using datasets including around 100K previously classified real and fake news, Zaeem et al. (2020) [11] assessed the difference between fake and genuine social media news. Several sentiment analysis methods were validated, and conditional probability was used to show the relationship between sentiment and accuracy. A statistical hypothesis test was also employed to ascertain the connection between truthfulness and mood. The technique revealed significant relationships between real news (positive sentiment) and fake news (negative sentiment), with a significance level of 99.999 percent. The authors released data and code publicly accessible for automatic fake news researchers and encouraged replication.

Dey et al. (2018) [12] generated a dataset with 200 tweets on Hillary Clinton and assessed their authenticity. The authors used prominent assessment measures to evaluate our framework's success rate and describe the outcomes of using an algorithm. The authors highlighted the interrelated study areas and future research objectives to detect fake posts and news on multiple platforms for social media.

De et al. (2020) [13] proposed a methodology for identifying data available on the internet, trawling data sources to map information in terms of the source's validity. The authors reviewed official social media accounts, and online views of data sources, conducted sentiment analysis, examined agency listings, and calculated scores for that news. The observed value, which is the foundation of their concept, determined the news's validity. This study proposed supervised learning to categorize distinct news articles based on predetermined criteria.

Cui et al. (2019) [14] present a deep embedded model to identify fake content and news which included users' latent emotions. To cope with diverse data modalities, the authors first utilized multi-modal networks. Second, the approach used an adversarial technique

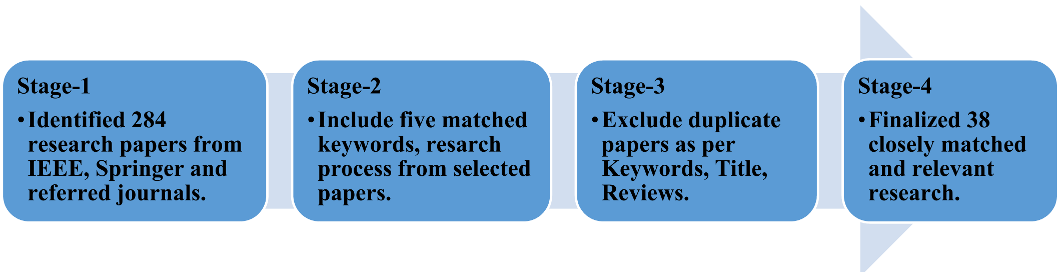


Fig. 2. Research process

Table 1
Classification of literature reviewed.

Research Keywords/Levels	1st	2nd	3rd	4th	Final
Sentiment Analysis	70	53	32	10	25.00 %
Social Media Post	66	49	29	9	22.89 %
Fake News	59	44	27	8	20.77 %
Distorted Campaigns	45	34	20	6	15.85 %
Machine Learning	44	33	20	6	15.49 %
	284	213	128	38	

to discover semantically meaningful spaces per data source. Third, a unique regularization loss was defined to put important pair embedding closer together. Extensive validation using two real-world datasets demonstrated the effectiveness in detecting false news, significantly surpassing the latest research methods.

Xu et al. (2020) [15] defined topic comprehension and domain rankings were used to recognize real and fake content, including posts and news on the basis of Facebook shares, reactions, or comments. The registration patterns, domain rankings, timeliness, and domain attractiveness of fraudulent and real news producers were all different, according to domain reputation research. The usage of phrases and word vectors has been found as a possible route for detecting fraudulent and genuine news.

Moral foundations theory identifies foundations that may be used to describe the theory and functioning in decision-making, as well as how information is seen and understood. Carvalho et al. (2020) [16] suggested developing a lexicon based on Brazil and Portuguese on the moral underpinnings theory, to determine sentiment in fake news content by identifying variations in the human dimension that may be utilized to distinguish between articles from credible sources and texts from low-reputation sites.

The major propagation of fake news, according to most experts, is the use of software robots or bots that communicate with human users automatically. Balestrucci et al. (2020) [17] presented the issue of categorizing real individuals on social media as credulous. The authors looked at individuals who had a lot of bots in comparison to their total range of social connections. This group of users was given extra attention in the study because they might be more exposed to malicious activities and could disseminate misleading information by spreading questionable content.

Especially in connection to emotions, Ajao et al. (2019) [18] focused on the characteristics of rumors and false news for automated identification. Empirical evidence led the study to suggest that misleading communications or rumors and the moods of online texts are correlated. The authors test their notion by contrasting it with text-only approaches for spotting bogus news that overlook emotion. Results from X's fake news collection revealed a clear improvement in false news posting and rumor identification.

Do et al. (2021) [19] offered a technique for spotting bogus news that takes social context news content into account. Using deep images, the writers looked at multiple news stories addressing different goals—either individually or together. This work used field layers and graph-based convolutional networks for exploiting core structural information of the contents. The writers use their knowledge of social topics to clarify the fundamental links. Results showing the efficiency and better performance of the proposed approach came from reputable datasets.

Apart from the output level under examination, Hirlekar et al. (2020) [20] looked at techniques, tools, and browser extensions. The study also looked at the general strategy to spotting bogus news and the feature extraction taxonomy, both of which are crucial for maximising natural language and machine learning algorithm accuracy.

Lin et al. (2019) [21] concentrated in creating machine learning models only based on text available in news sources in order to automatically identify bogus news. The authors offered a neural learning approach to detect false news and gave a framework for feature extraction to create popular models like Random Forest and XGBoost. The XGBoost models output for accuracy of political and celebrity news items to be better as compared to other models, respectively, by 16.44 % and 13.15 %, when the models were assessed against seven baselines, the scientists found.

With the text-based sequencing evaluated in one direction, many practical approaches for spotting false news depend on sequential neural networks to include fresh information and social information. To represent the main information of false news items, the authors suggested a bi-directional model competent of improving the performance of the classifier while keeping lexical and long-distance linkages in phrases. Combining numerous concurrent blocks of a single layer neural model with dynamic kernel filters and widths, Kaliyar et al. (2021 [22] presented a reversible deep learning method). The proposed model proved to be better than the current models with a classification accuracy of 98.90 percent, according to the findings.

Islam et al. (2020) [23] reviewed research dealing with research issues and methodologies. While critical, automated misinformation detection is challenging to achieve since sophisticated models are required to determine connected or unrelated reported information to be fake or genuine. The three main types of misinformation that have been investigated so far are deliberate misinformation, fake news, and rumor identification. Therefore, the authors provided a comprehensive evaluation of automated misinformation identification on fake news, fake statements, spam, rumors, and misinformation about the above concerns. Deep learning was discovered to be a flexible and efficient method for detecting cutting-edge fakes. The authors also identified some unresolved difficulties that are now impeding real-world application and recommended future initiatives in this area.

Due to its dynamism, detecting fake news is difficult. Meesad et al. (2021) [24] presented a methodology for detecting reliable fake news. The data collecting and machine learning model construction phase are the two phases of this study.

Singh et al. (2021) [25] put up an effective and successful multi-modal approach for spotting fake images on microblogging platforms. The suggested method modelled photo identification using an expressive convolutional neural network and textural analysis using a phrase converter. After going through deep levels, the visual and textual feature encoding is combined to avoid deceptive images. The efficiency of the model was evaluated using publicly available microblogging data; accurate predictions of 85.3 % and 81.2 % were noted. Furthermore evaluated is the approach employing a freshly produced X dataset comprising images of significant events in India until 2020. Simulations demonstrate that the proposed model beats the multi-modal approaches of the current framework.

Braşoveanu et al. (2020) [26] put up a conceptual approach for spotting fake news. It is grounded on relational elements including facts derived directly from the language, objects, and emotions. Studies on short texts with varying degrees of validity show that adding semantic knowledge greatly increases accuracy.

Developing efficient and thorough algorithms for false news identification has become a major challenge even if there are several fake news databases. Li et al. (2021) [27] were able to rapidly recover and add significant discoveries by incorporating a network layer into a semi-supervised, self-learning, deep neural network, thus assisting the neural network to acquire positive sample instances and so increase its dependability. Experiments showed that the model exceeded present standard machine learning and data mining methods.

According to Kaliyar et al. (2021) [28], user-based relationships and a situational collection of people with similar ideas can help identify bogus news. The authors examined the social media news substance for any existence of echo-chambers to identify false news. Because they are unsupervised, traditional methods to detect fake content are typically utilized in conjunction with traditional ML models. The researchers created the simulation using a distinct set of failures and characteristics in each thick layer. News material and social content were categorized together and individually using a deep neural network with hyper-parameters. The results demonstrate that the validation accuracy of the technique, when tested on real-world false news datasets, was 92.30 percent, exceeded the fake news acceptable detection baseline.

Hold-out cross-validation was utilized by Jiang et al. (2021) [29] to test the effectiveness of deep and machine learning models on fictitious and real news datasets of varying size. To reduce complexity, Umer et al. (2020) [30] presented a hybrid neural network-based framework. This combined LSTM characteristics with convolutional neural networks (CNNs) using principal component analysis and Chi-Square. The authors included four categories of attitudes in the data from the Fake News Challenges website - agree, disagree, dispute, and unimportant—were used to construct the explanation. PCA and chi-square get curvilinear qualities as input, and these algorithms offer more contextual information for the detection of bogus news. Finding out how a news item responds to its headline is the aim of this study. The suggested method yields improvements in accuracy and F1 scores of 4 % and 20 %, respectively. According to the findings, PCA performs 97.8 % better than Chi-square and other cutting-edge techniques.

Computationally stylistic natural language processing, which employed ML methods to identify bogus news stories, was created by Oliveira et al. (2020) [31]. To determine if 33,000 X postings were real or fraudulent, the research examined them. The suggested approach showed less overhead and may offer a greater degree of confidence index for differentiating between real and fraudulent news.

Verma et al. (2021) [32] presented ML-based, two-phase benchmark strategy to identify fake news identification classification based on word-embedded using linguistic features. The first step preprocesses the data gathering and uses linguistic characteristics to assess the news material's validity. In the second stage, the grammatical retrieved traits are combined and voting classification is used. Its methodology which used a variety of data sets to get an objective classification result was validated using a special dataset of over 72,000 publications. Studies show that the model accurately classifies news as authentic or false with 96.73 percent accuracy; this outperforms bidirectional encoder representations by 1.31 percent and convolutional neural network models by 4.25 percent.

The behavior and frequency of bots on Twitter (now X) was investigated by Pastor-Galindo et al. (2020) [33] during the general election in Spain in November 2019. The authors classified the users as humans or bots to analyze the activities based on the volume of traffic generated, pre-existing connections, and the users' political affiliation and attitude toward the positions of the major political

Table 2
Fake news detection techniques.

Techniques	Approach	Method	Indicator
Textual analysis	Analyze linguistic features of headlines, articles, and media posts	NLP techniques, sentiment analysis, language pattern recognition	Unusual language patterns, sensationalism, inconsistency, or exaggeration
Social Network Analysis	Examining the spread and propagation patterns of information within social networks	Graph theory, network centrality analysis	Rapid dissemination, clustering of misinformation, and high engagement with suspicious sources.
Source Credibility Analysis	Assessing the credibility and reliability of news sources	Source reputation scoring, fact-checking, historical accuracy analysis	Reputation of the publisher, fact-checking results, historical track record
Multimodal Approaches	Integrating multiple data modalities, such as text, images, and audio	Fusion of textual and visual features, content-based image analysis	Inconsistencies between textual and visual content, manipulation of multimedia elements.
Machine Learning Models	Employ supervised learning for classifying news as genuine or fake	Random Forest, Support Vector Machine (SVM), Neural Networks	Features derived from textual and metadata, training on labeled datasets
Deep Learning Techniques	Utilizing deep neural networks for more complex pattern recognition	CNN, LSTM, and Recurrent Neural Networks (RNN).	Sequential dependencies in text, hierarchical representations.
Fact-Checking and Verification	Cross-referencing information with external fact-checking databases or reliable sources	Automated fact-checking algorithms, and manual verification by experts.	Discrepancies between the news content and verified facts.

parties. The data indicated a sizable portion of the bots contributed in elections, backed by major political organizations.

Researchers frequently combine numerous strategies to handle the complexity and difficulty connected with spotting misinformation, as fake news detection is a continuously expanding area. Every strategy adds to a comprehensive understanding of the issue, and continuous research attempts to increase the precision and effectiveness of detection techniques. Existing techniques for fake news detection employ a variety of approaches, leveraging computational methods, ML, and NLP to identify misinformation as presented in Table 2.

3. Beyond the Illusion of fake social media posts

During US and Indian elections or global events like the COVID-19 epidemic, they are sharing fake posts, and fake news spreads like wildfire over social media. Russians were alleged to use Instagram, Facebook, and X to spread conspiracy theories, and fake information, and fuel or manipulate opinions. The impact of this is immense, as fake news is known to spread fast and wide as compared to actual information [34]. Retweeting of fake posts was 70 % more as compared to true posts on X, which reached 1500 users at least 5 times faster. This influence was more noticeable in political news. Software robots or Bots also spread information (both true and fake) at the same speed. It was also found that users retweet fake information more in comparison. Users sharing fake tweets and information were likely lazy and distracted instead of being biased [35]. When rating the accuracy of Facebook news, those with analytical thinking were able to differentiate the fake headlines from true, irrespective of political opinions. Politicians also fuel misinformation to gather votes. Users often acknowledged political candidates speaking and distributing palpable lies [36], Some users saw such candidates as more dependable. Social media posts presenting disputed information should be tagged with a warning label as per Rand et al. (2020) [37]. Since users imply any and every piece of information without any labels is true. However, fake headlines with no tags could be considered truth, so having verification tags for true headlines is not a viable fix. Opinions and views can be skewed on social media since often people are inclined to live in biased silos and are happy with partial truth. This feature tends to distort thinking and can influence electoral views and voting.

To measure and then analyze the manipulated posts, Dean Eckles (2020) [38] presented a defense method against future interferences. This process involved classifying social media manipulations. Voter behavior datasets were combined to calculate the effectiveness and the impact of the fake posts. This helped determine the changes and consequences of voting behaviors. It was found that people don't care about what is shared as tweets or posts, irrespective of whether they are true or fake, and only focus on getting attention from others instead of thinking about sharing accurate and true information. Fake posts were more likely to be identified by social media users and make decisions and use their judgment irrespective of political views or headlines. Social media advertising is aided by fake posts, e.g., Facebook marketing that enabled advertising agencies to pay and target specific user groups, for example, the 2018 US elections were manipulated by Russia which pushed fake propaganda campaigns to sway voters. Research by Catherine Tucker (2020) [39] concluded that only after Facebook's advertising detection intercepted fake articles, there was an almost 75 % reduction in the sharing of fake news. The same system also helped detect anti-vaccination posts that claimed the various COVID-19 vaccines were ineffective and caused further issues in children.

In March 2023, from a news survey on Fake Digital News by Statista [40] involving more than 86,100 respondents aged 15–60 years across nine Indian languages, it was found that over 60 % of participants said they occasionally came across potentially fake Internet content. While 3 % of the customers polled said they had never come across potentially fraudulent news on the internet as illustrated in Fig. 3. In India, the frequency of occurrences involving fake news has increased recently.

4. Research methodology

This research focused on identifying fake news using Sentiment Analysis as well as Recurrent Neural Networks. Sentiments are expressed with emotions, judgments, insights, and views by people. Emotion is often a sudden conscious or unconscious reaction depending on the situation. Emotion in text format can be viewed as the writer's impact on how the words are selected when expressing certain emotions or the ways readers interpret the posted content based on their ability to analyze or as per their current

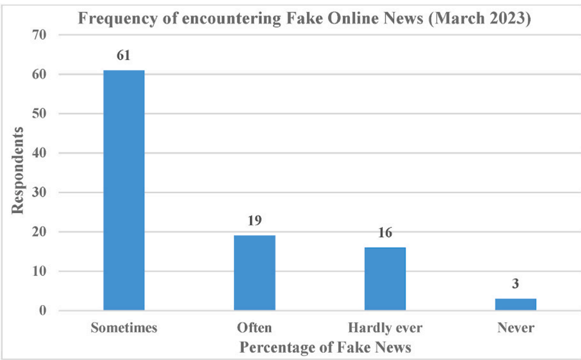


Fig. 3. Frequency of encountering Fake Online News [40].

state of mind when reading the post. Fig. 4 takes this concept further to present the mind map with various categories of sentiment analysis at the document, sentence, or aspect level. From a detection perspective, two methods are proposed, the first involves the lexicon approach which uses either a dictionary or a corpus and the second approach involves Machine Learning which is the base of this research.

The dataset used for this research involved X posts and comments, involving 15,927 reviews of which 2591 were classified as positive, 8971 were considered negative and the remaining 4365 were categorized as neutral. The dataset also included 862 emoticons of which 262 were positive, 529 were negative and 72 were neutral. These classifications were further processed to improve the accuracy of sentiment detection process in two stages. First stage involved data being tokenized, during which links, URLs, digits, and stop-words were eliminated, even as emoticons and punctuation marks were allowed to be kept. In the second stage emoticons and punctuation were removed. Then the sentiment score was calculated. Thus, two distinct datasets as involved in this research - one related to sentiment analysis on Twitter data and other related to false new content. The sentiment data involves X posts and comments, while the fake news data has different samples. The correlation between the fake news and sentiment data is not explicitly specified in the information given.

The sentiment dataset and the fake news dataset may be entirely independent, collected for different purposes or from different sources. In this case, they serve distinct analytical objectives and any relationship. These datasets are subsets of a larger dataset, and the information provided focuses on specific aspects related to sentiment analysis and fake news detection. These datasets are also part of a sequential or iterative analysis, where sentiment analysis is performed as a preliminary step to understand the emotional context before delving into the identification of fake news. The datasets are related in their contribution to the overall research framework.

The authors applied natural language to identify fake news by converting words into numbers. These numbers are utilized to train the proposed AI/ML models for predicting news with various news text-based datasets. This output for the framework is binary and useful for media organizations to determine if the news is false (zero, 0) or true (one, 1). Steps for the AI/ML research methodology are illustrated in Fig. 5 and the methodology is described below.

Step 1. Import Datasets and libraries and perform Exploratory Data Analysis

The dataset and libraries are imported in this step to kick-start exploratory analysis. Python libraries like matplotlib, TensorFlow, NumPy, and seaborn are imported to perform visualization, processing, and computation. Keras and TensorFlow are used in the implementation of NLP to predict fake news. The implementation is performed on Google Collab, importing the fake and true data. The fake dataset contains fake news data, and the true dataset is comprised of genuine news. These two datasets are then clubbed together, and the prediction process is applied to this combined dataset.

Step 2. Perform Basic Visualization

One extra column is added to the dataset to hold binary values of 0 (news = fake) or 1 (news = real) and primed for training the model. Data cleaning is performed in which stop words or words with 2 or fewer characters are removed. Such data cleaning is necessary because if there is some garbage in the data then the results may be affected. The real and fake news are clubbed together, and the data is cleaned. Total words in the dataset are calculated and a list of words is generated along with unique words, and these are joined together to form a string. Data visualization is performed on this combined dataset as illustrated in Fig. 6a with the X-axis as 'subject', which displays that political news having the count on the Y-axis. Fig. 6b presents the Ture and Fake new on X-axis and the count being almost equal to the real news count on the Y-axis.

Word cloud for the real news text is plotted to visualize the types of words used in the real news as shown in Fig. 7. These images present the word cloud of real news observed for the most frequently used words in real news as Trump, Donald, White House, and Government. This visualization aids in observing the words in real news. Next, the word cloud for fake news text is plotted. This also illustrates the words in fake news such as State Reuters, Said, Year, Like, and Time.

The length of the maximum document is calculated to create word embedding with 4405 being the maximum words in any document, Fig. 8 plots the word count distributions in the text.

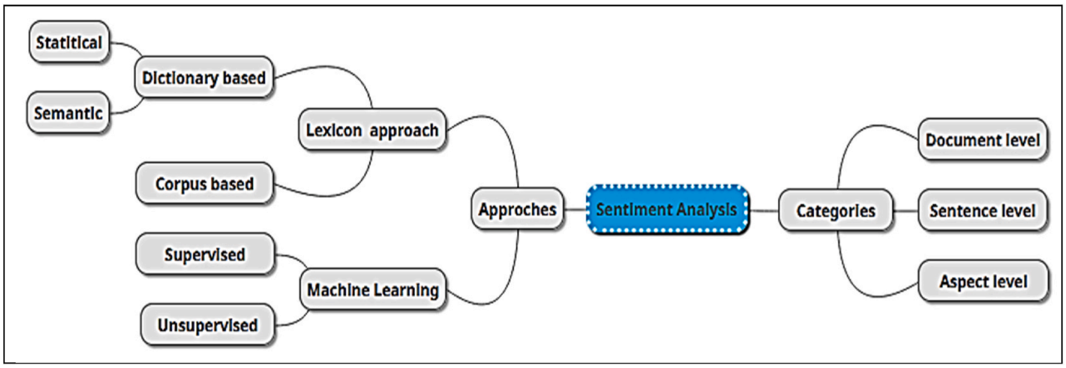


Fig. 4. Sentiment analysis approaches & categories

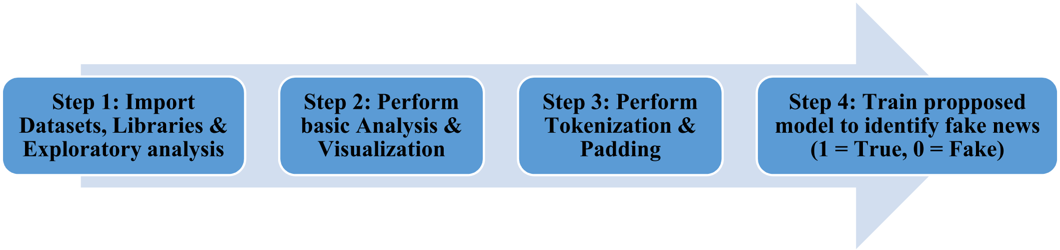


Fig. 5. Proposed AI/ML methodology

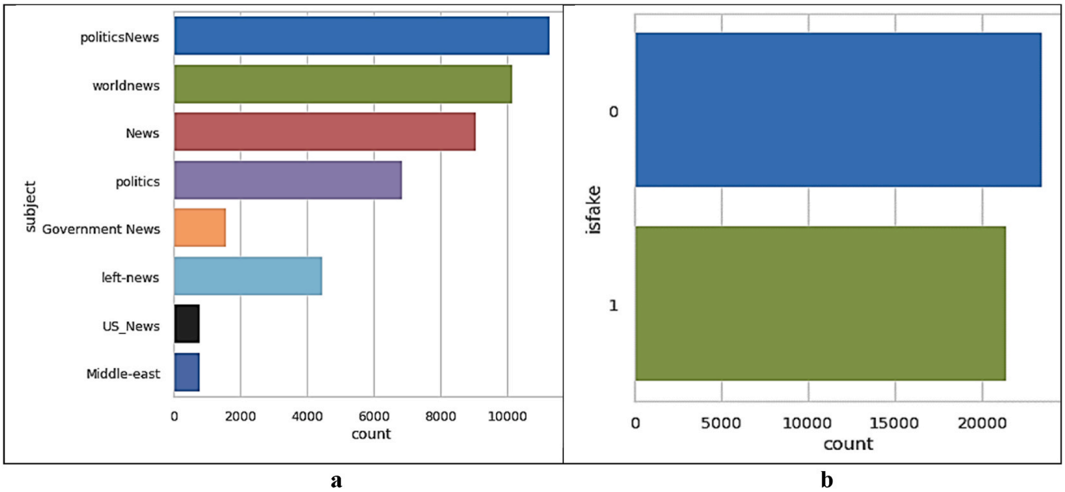


Fig. 6. a: Subject samples Fig. 6b: Fake & true news count

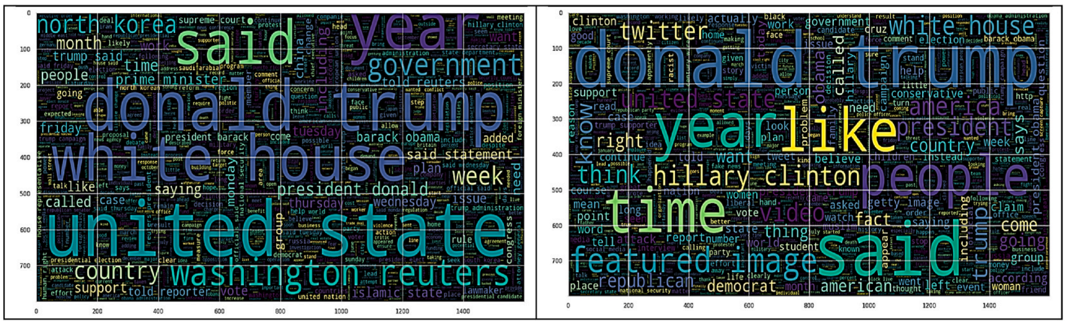


Fig. 7. Word cloud of real & fake news words

Step 3. Perform Tokenization & Padding

The entire dataset is segregated into test and training sets, then tokenization is done to create sequences of tokenized words. Tokenizer vectorizes the text corpus by changing text into a sequence of integers. Padding is added to ensure data is free from anomaly in a realistic and free format.

Step 1: Create Tokenizer
    Tokenize Text Words → Sequence of tokenized text_words;
    Tokenizer t = t $\sum$ text_words = sum of words;
    Tokenizer Fit t(fit) = fit_on_text_words(a_train);
    Train Sequence t(seq) = t.word_texts_to_sequence(a_train);
    Test Sequence t(test) = t.word_texts_to_sequences(a_test);
    Step 2: Add Padding

(*continued on next page*)

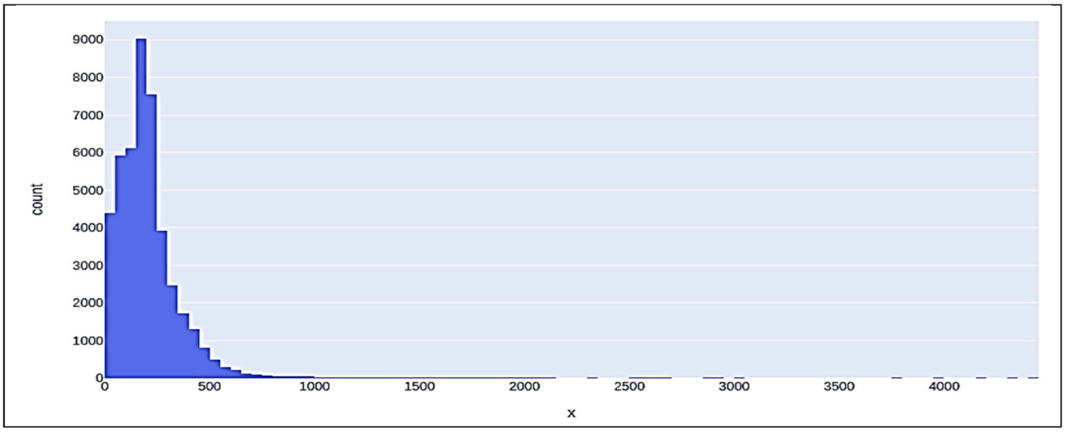


Fig. 8. Distribution of words in text

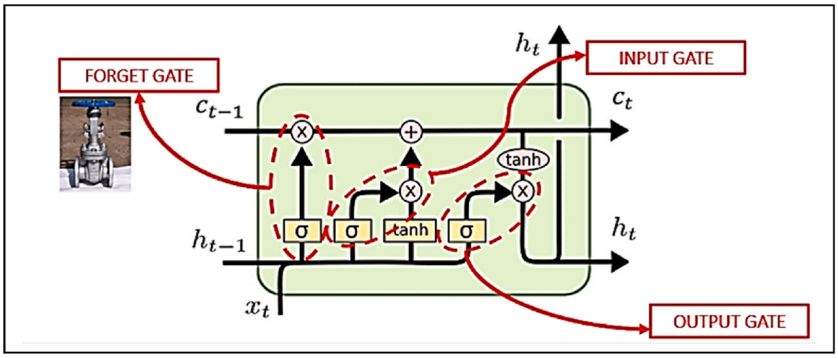


Fig. 9. Architecture of LSTM [37].

(*continued*)

Define Padding lengths:
Max length m = 4405
Min length n = 50
Padded Training → p(train) = pad_sequence (t(seq), m, pad('post), truncate(post));
Padded Testing → p(test) pad_sequence (t(test), n, truncate('post));

Step 4. Train the Model to Identify Fake News

This phase employs the deployment of a feed-forward neural network to map a fixed-size input to a fixed-size output. The authors selected the RNN model for training because the RNN, which is a form of the deep neural network, can be constructed to consider time dimension by having a storage, or feedback loop. This neural network, commonly known as the Vanilla system, works by mapping inputs to outputs. There are a lot of inputs when there are a lot of outputs, and all the neurons are fully linked to all of the neurons in the next layer. When it comes to foot-forward convolutional neural networks which don't have any time dependence or memory impact, the data just propagates from the left-hand side to the right-hand side, which is a big disadvantage. The hidden layer of an RNN comprises a temporal loop in which it not only produces output but also feeds itself. Time is introduced as a new dimension. Because RNN can remember what occurred in the preceding timestamp, it works well with text sequences. RNN is a special type of model, which feeds forwards the ANNs as constrained with a fixed number of input and output. For example, CNN will have a fixed-size image and generate a fixed output. Feedforward ANN has a fixed configuration, i.e., the same number of hidden layers and weights. RNN offers a huge advantage over feedforward ANN-like sequences in inputs and outputs.

The authors have used the LSTM model in the implementation. LSTM stands for Long Short-Term Memory model. Because they avoid the vanishing gradient problem, LSTM networks outperform RNN models. During backpropagation, the Vanishing Gradient Problem is computed. We compute the network's derivatives by going from the outermost layer back to the starting layers via backpropagation. Throughout this computation, the variables from the final stages are multiplied by the derivatives from the early layers using the chain rule. Because the gradients are decreasing exponentially, the weights and biases are no longer adjusted. This behavior causes the Vanishing Gradient issue, which LSTM solves. RNN fails to build long-term dependencies in practice. By default, LSTM networks are RNNs that are intended to remember long-term interconnections. LSTM can remember and recall information for a long time. The LSTM has gates that permit or prevent information from going through.

When the LSTM model [42,43] comes across a news story that is primarily negative in tone and has emoticons that convey doubt, it uses associations it has learned throughout training to determine the likelihood that the content is bogus. The LSTM model becomes more skilled at capturing the complex links between sentiment patterns and the authenticity of material by incorporating sentiment information into its design and training procedure [44]. This allows for the identification of false news with greater knowledge and more educated conclusions. The sample code utilized in this research is presented below for reference.

```
# Pseudo-code for LSTM Model with Sentiment Analysis
  #Step 1: Sentiment Feature Extraction
  sentiment_features = extract_sentiment_features(text_data)
  # Step 2: Embedding Sentiment Features
  embedded_data = embed_sentiment_features(text_data, sentiment_features)
  # Step 3: Model Architecture
  model = build_lstm_model(embedded_data)
  # Step 4: Joint Learning of Text and Sentiment
  model.train(training_data)
  # Step 5: Decision-Making Process
  def predict_authenticity(new_content):
    # Extract sentiment features for the new content
    new_sentiment_features = extract_sentiment_features(new_content)
    # Embed the sentiment features into the input data
    embedded_new_data = embed_sentiment_features(new_content, new_sentiment_features)
    # Make a prediction using the trained LSTM model
    prediction_score = model.predict(embedded_new_data)
    return prediction_score
  # Step 6: Threshold Setting
  threshold = set_threshold(training_data)
  # Step 7: Post-Processing and Validation
  def classify_content(prediction_score, threshold):
    if prediction_score > threshold:
      return "Genuine"
    else:
      return "Fake"
  # Example Usage
  new_content = "A news article with negative sentiment and skeptical emoticons."
  prediction_score = predict_authenticity(new_content)
  classification_result = classify_content(prediction_score, threshold)
  print("Classification Result:", classification_result)
```

As illustrated in Fig. 9, the sigmoid architecture involves input and output gates and a pointwise multiplication operation. The output range is from 00.1, where 0 = do not allow_any_data_to_flow and 1 = allow_everything_to_flow.

For LSTM to perform and calculate the prediction score:

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right) \qquad \text{Equation 1}$$

Equation (1) describes the forget gate in an LSTM unit, this is crucial component for handling long-term dependencies in sequence prediction The forget gate takes the previous hidden state and the current input, multiplies them with learned weights (W_f), adds a bias (b_f), and then applies a sigmoid function. The resulting value (f_t) determines how much information from the previous cell state (c_(t-1)) should be retained (closer to 1) or forgotten (closer to 0). This allows the LSTM to selectively remember, or discard information based on its relevance for the current prediction.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_t) \qquad \text{Equation 2}$$

Equation (2) represents the input gate in an LSTM unit for controlling information flow within the cell. The input gate analyzes both the information the LSTM remembers from the past (h_(t-1)) and the new information in the current input (x_t). Based on these, it determines how much of the current input should be allowed to influence the cell state update. A value closer to 1 allows more influence, while a value closer to 0 restricts the update. The forget gate (f_t) and the input gate (i_t) work together as the forget gate decides what information to forget from the previous cell state. The input gate decides how much new information from the current input to consider for updating the cell state. This allows the LSTM to selectively incorporate relevant new information while maintaining important past information in the cell state.

$$C_t = (f_t * C_{t-1}) + \left(i_t * C_t^{\sim}\right) \qquad \text{Equation 3}$$

Equation (3) represents the cell state update in a Long Short-Term Memory (LSTM) unit, combining the outputs of the forget gate (f_t) and the input gate (i_t) along with other elements to determine the new cell state (C_t) at the current time step (t).

$$C_t^{\sim} = tan\left(W_c \cdot [h_{t-1}, x_t] + b_t\right. \qquad \text{Equation 4}$$

Equation (4) represents the calculation of the candidate cell state (Cˆ∼_t) in a Long Short-Term Memory (LSTM) unit. This candidate state holds new information that could potentially be added to the actual cell state (C_t) at the current time step (t). By using the candidate cell state and the forget and input gates, LSTMs can effectively control the flow of information and selectively update their memory with relevant new information.

$$o_t = \sigma\left(W_f.\ [h_{t-1}, x_t] + b_o\right) \quad \text{Equation 5}$$

Equation (5) describes the output gate in LSTM unit. It determines how much of the current cell state (C_t) should influence the output (h_t) at the current time step (t). The output gate analyzes both the information the LSTM remembers from the past (h_(t-1)) and the current input (x_t). Based on this context, it determines how much of the current cell state (C_t) should be used to influence the output (h_t) at the current time step. A value closer to 1 allows more information from the cell state to pass through, while a value closer to 0 restricts its influence.

$$h_t = o_t * tanh(C_t) \quad \text{Equation 6}$$

Equation (6) represents the final output calculation in LSTM unit at time step t. The LSTM applies the tanh function to this filtered information (o_t * C_t)). This ensures the final output (h_t) has a bounded range (−1 to 1) and captures the most relevant aspects of the cell state based on the output gate's control.

This final step completes the LSTM cycle, where it processes the current input, updates its internal memory (cell state), and generates an output that reflects the most relevant information for the current time step.

5. Proposed framework

For the Sentiment analysis algorithm, pre-processing of the X dataset is performed by tokenizing and removing the links, URLs, digits, and stop-words. The second level of processing is performed to remove the emoticons and punctuation and emoticons. The proposed algorithm extracts word features from the dataset and emoticons from the first level dataset using emoticon lexicon and similar word features except for emoticons from the second level dataset. For every feature extracted and applied using the proposed algorithm in the two datasets, the scores are calculated and compared with the machine learning result with deep learning results to select the best output.

For the Machine learning framework, initially the Embedding layer. An embedding layer learns the low dimensional, continuous representation of input discrete variables with the total number of words as 108704. After embedding the layer, a bi-directional RNN and LSTM layer are added with 128 input parameters as presented in Fig. 10. The next two dense layers are added to the model with RELU and Sigmoid as the activation functions.

The optimizer used in the implementation of the model is the 'Adam optimizer' whereas the loss is binary cross-entropy. The metrics here are accuracy and then would be able to say model that summary and that will print out the summary. The dataset with 14 million trainable parameters has the first embedding layer followed by the LSTM part of the bi-directional layer and then has the two dense layers later. The total number of words is 108,000 with a batch size of 64 validation split to point to be 0.0.1 and epochs. The validation split is set at 0.1 since the training data is divided further into 10 % for cross-validation and 90 % to train the model. The research dataset started with the entire data set and was then divided into training and testing datasets. The testing dataset is the subset of the data that the model has never seen before during training, this happens after the moderate strain. Next, the training data is split and plated into essentially 90 % to in the model and 10 % to perform cross-validation. Then cross-validation is reapplied to ensure the model does not overfit the training data as the model is being trained. Now after every epoch, the data is run through the model to validate if the letter on that validation data set is going down or not. The pseudo-code to build this framework is presented below.

```
Step 1: Build a Sequential Model → build_model = sequential ()
    Step 2: Add Embedding Layer → model_add(embed(word_total, dim_output = 256))
    Step 3: Add Bi-Directional RNN and LSTM Layers → model_add(bidir (LSTM(256)))
    Step 4: Add Dense Layer → model_add(dense_layer(128, acti = 'relu'))
    Step 5: Train Model → model.fit (padded_train, y_train, batch (size) = 128, validation (split) = 0.1, epochs = 5)
```

For sentiment analysis, this research used rule-based training like VADER from the NLTK library for which the NLTK and VADER are utilized. For the Machine Learning model for Fake News Detection, the authors used the example with scikit-learn for training a fake news detection model prepared the dataset, and selected the proposed framework.

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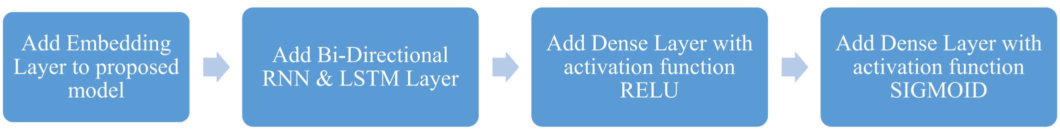

Fig. 10. Proposed framework

(*continued*)

```
# Sample dataset with labels (1 for fake, 0 for real)
    data = [
        ("Fake news text 1″, 1),
        ("Real news text 1″, 0),
        # Add more data …
    ]
    texts, labels = zip(*data)
    # Vectorize the text data using TF-IDF
    vectorizer = TfidfVectorizer()
    X = vectorizer.fit_transform(texts)
    # Split the dataset into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, labels, test_size = 0.2, random_state = 42)
    # Train a Random Forest classifier
    clf = RandomForestClassifier()
    clf.fit(X_train, y_train)
    # Make predictions
    y_pred = clf.predict(X_test)
    # Evaluate the model
    print(report)
```

6. Results obtained

Two different experimental modalities were used in this research: one focused on word texts and the other on emoticons, and the other solely examined text and emoticons. While both machine learning and deep learning methods were used to assess the data, only machine learning was used to study the textual data. Comparing text analysis alone to emoticon lexicon adaptation and other characteristics improves the quality of the analysis of both texts and emoticons. From the experiments performed, this research delivered 99.68 % accuracy in only two epochs that involved 14,210,305 trainable parameters. Table 3 presents the statistics for the type of layer, output shape, and parameters.

Total params: 14,210,305

Trainable params: 14,210,305

Non-trainable params: 0.

Results obtained indicate the LSTM and CNN deep learning algorithms perform better than machine learning algorithms with higher accuracy for sentiment analysis as presented in Table 4.

The research also reviewed existing methods and found only some related to this research, these were then compared for fake news detection with the proposed framework. Text and emoticons deliver 61 % for existing systems while this research achieved an accuracy of 84 %. When analyzing only texts other methods displayed an accuracy of just 57 % while the proposed framework delivered an accuracy of 73 % as presented in Table 5.

The authors validated the Sentiment Analysis results with Tweet Sentiment Visualization [40], focusing on visualizing the sentiment of tweets on X. The objective of using X was the potential displayed for impacting society as an easily available, online communication tool. The authors focused on Sentiment, Tag Cloud, and Timeline. Topic, sentiment, frequent terms, etc visualize the collected tweets. Individual tweets are represented as circles with colors, size, brightness, and transparency to illustrate different sentiment details about the tweet. The polarity score is shown in the following image as a mix of each tweet circle's color, size, brightness, and transparency. Every circle represents a single tweet, and the message's emotion polarity is translated to the circle's visual characteristics. The polarity of sentiment is represented by color, where warmer hues denote a good sentiment and colder hues a negative sentiment. The size of a tweet reflects its popularity or level of engagement. The intensity or strength of sentiment is reflected in transparency and brightness, where brighter and more opaque circles indicate stronger sentiments.

The authors have provided readers with a clear reference to understanding the sentiment subtleties depicted in the scatterplot by updating the caption to explicitly describe these visual mappings. A subset of tweets' manually annotated ground truth sentiment labels is compared to the sentiment analysis results. We may evaluate the accuracy of our sentiment analysis system against this comparison as a baseline. We do cross-validation experiments on several subsets of our dataset to evaluate the generalization performance of our sentiment analysis model. This makes it more likely that our model will function well across various data segments. To confirm the efficacy of our method in a wider setting, the authors compared the sentiment analysis results with datasets or benchmarks that are already available. The sentiment tab illustrates the tweets in the overall sentiment as the emotional scatterplot, ranging from

Table 3
Statistics of parameters.

Type of Layer	Output Shape	Parameters
Embedding	128	13914112
Bidirectional	256	263168
Dense	128	32896
Dense_1	1	129

Table 4
Comparing accuracy % for machine learning and deep learning algorithms.

Algorithms		Accuracy %
Machine Learning	Random Forest	75 %
	Native Byes	56 %
Deep Learning	LSTM	87 %
	CNN	83 %

Table 5
Comparing existing & proposed framework.

Sentiment Analysis	Existing methods	Proposed Framework
Text + Emoticons	61 %	84 %
Text only	57 %	73 %

horizontal and vertical axes as illustrated in Fig. 11 for the tweet ‘Covid-19’ textual word.

As seen in Fig. 12, a tag cloud displays words that appear often in emotional areas such as upset in the upper left, pleased in the upper right, relaxed in the lower right, and dissatisfied in the lower left. The magnitude of the word indicates how often it appears in tweets in that emotional zone.

The timeline depicts the period during which tweets were sent, with nice tweets appearing in green above the horizontal plane and bad tweets appearing in blue below the horizontal plane. The height of the bar indicates the number of tweets that have been published over time as illustrated in Fig. 13.

For machine learning, the authors used the sigmoid activation function in the open, with the prediction as a problem. The threshold is set as 0.5 and with the proposed framework, the research achieved an accuracy of 99.68 % on the testing data. For a visual representation, a confusion matrix is plotted as presented in Fig. 14. This represents the actual ground truth and the comparison of the prediction value and the actual value. The confusion matrix shows that the trained model for two epochs successfully reached an accuracy of almost 99 %.

7. Discussions

Recent researchers have focused on defining and identifying fake news tales propagated on social media. To reach this goal, these studies look at a range of variables obtained from news stories, including primary and social networking site posts. In addition to examining the major characteristics presented in the literature for fake news detection, the authors suggest many new features and analyze the prediction accuracy of current approaches and attributes for the identification system of fake news. Our results provide fascinating insights into features’ utility and significance in detecting fake news. In the run-up to the 2022 elections in India, the effectiveness of the proposed framework was tested. During the campaign season, a significant disinformation campaign unfolded on various social media platforms, targeting the leading candidates. This campaign involved the spread of fake information, manipulated media, and divisive narratives that aimed to influence public opinion negatively.

To detect and stop this misinformation campaign, this proposed ML and sentiment analysis platform was used in conjunction with independent fact-checkers. The spike in un-favorable sentiment linked to the false narratives that were directed at the candidates was quickly identified by the sentiment analysis algorithms of the framework. Alerts were created and distributed to fact-checking groups so that the false information may be quickly corrected. On a larger scale, reliable information may be used to change public opinion and effectively combat misinformation tactics. This may act as a concrete example of how our approach can be used in real-world scenarios, highlighting its importance in defending democracy and maintaining the integrity of one of the most significant elections in history. This indicates that, in the context of the elections, the suggested framework may have practical ramifications.

The integrity of democratic processes and public confidence may be seriously jeopardized by false information campaigns, for which our framework offers a potent early detection tool. Real-time social media platform detection and countering of distorted campaigns and fake news could make use of our framework to proactively detect and flag potentially misleading content, thereby decreasing the spread of fake news and greatly enhancing the information ecosystem on these platforms, guaranteeing more accurate and dependable content. This study has the potential to significantly improve the democratic process by making political campaigns more resilient against misinformation efforts. Our study’s use of a small data set was one of its limitations, which could have limited how broadly our findings could be applied. This study effectively created a strong framework for identifying skewed campaigns and bogus social media news by fusing machine learning and sentiment analysis methods. The results are in line with the findings of previous researchers who discovered that sentiment analysis and machine learning work well together to detect misinformation. The authors evaluated other research in similar areas to validate the performance of the proposed approach. The results demonstrate that the proposed paradigm is superior to other similar frameworks, as shown in Table 6, which presents the comparison of similar methods.

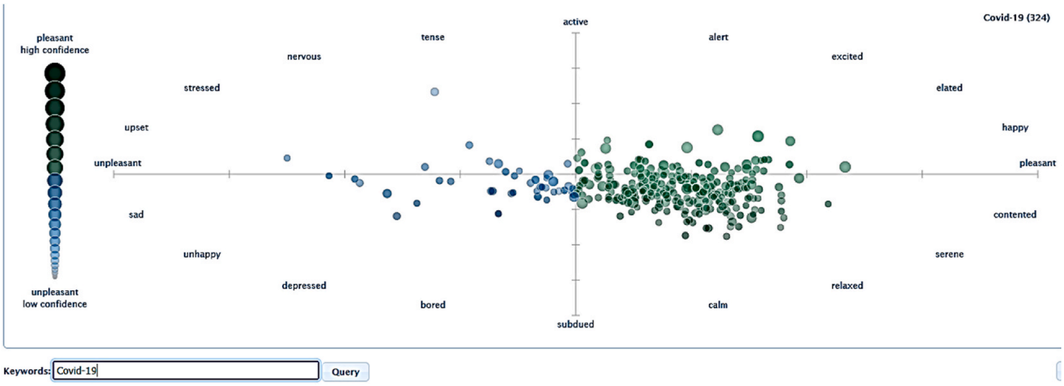

Fig. 11. Sentiments for 'Covid-19' using Tweet Sentiment Visualization [41].

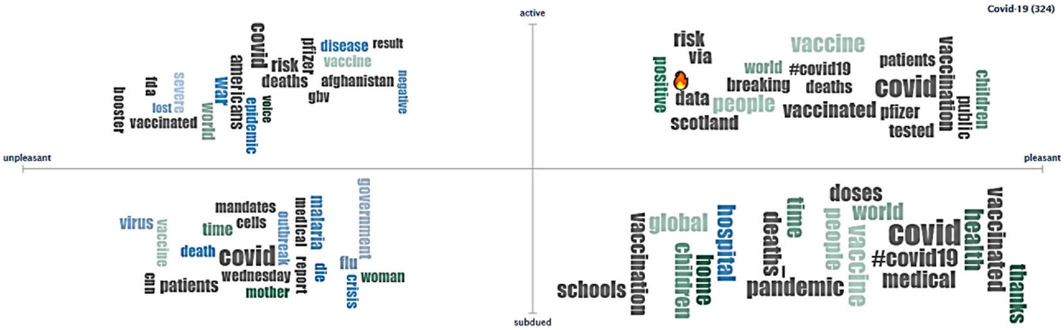

Fig. 12. Tag cloud for 'Covid-19' with tweet sentiment visualization [41].

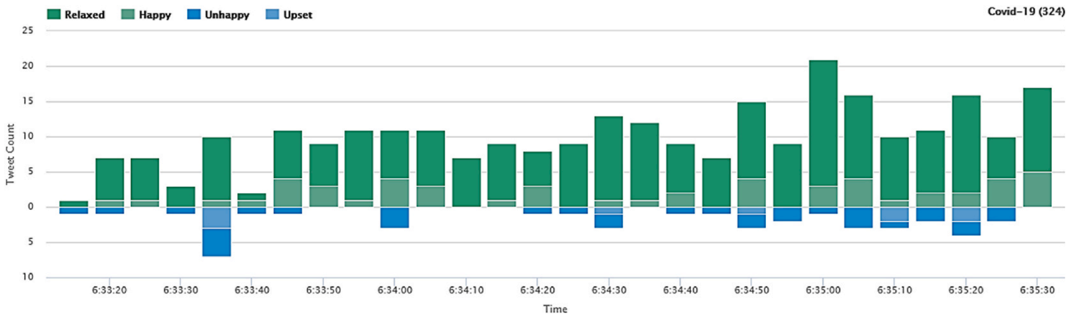

Fig. 13. Timeline for 'Covid-19' using Tweet Sentiment Visualization [41].

7.1. Limitations and recommendations

While being effective, the sentiment analysis method employed in this research might have overlooked certain nuanced forms of deceptive language and emotional expression on social media. Future studies could focus on expanding the dataset to include a broader range of social media platforms and languages to improve the framework's cross-cultural applicability. Exploring the use of more advanced natural language processing techniques, such as deep learning models, may enhance the accuracy of disinformation detection. Some of the major limitations are listed as follows.

- Dataset Limitations: potential biases, lack of representativeness, and challenges were faced during data collection. To address these issues related to the scope and diversity of the data, and improving the dataset in future research, incorporating additional sources, ensuring better geographical representation, or expanding the temporal scope is recommended.
- Ethical Considerations: freedom of speech and potential biases in fake news detection are two major ethical issues and new unique strategies for dynamic and ongoing review and user empowerment can emphasize the need for transparency and user involvement in refining the model.

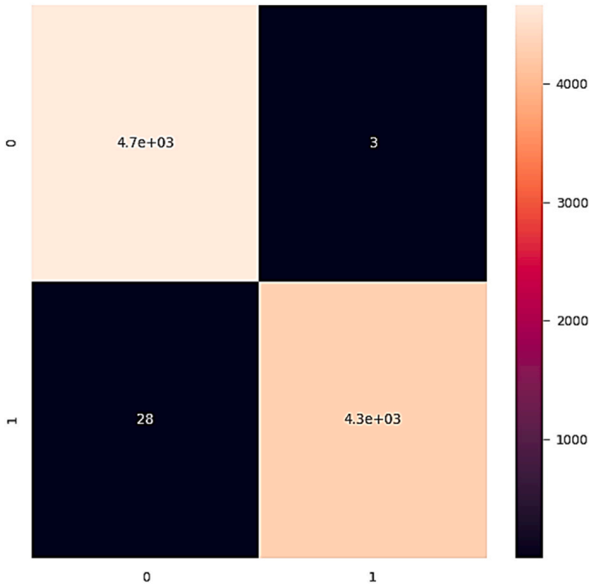

Fig. 14. Confusion matrix

Table 6
Comparative Analysis with similar approaches.

Methodology	Accuracy
Shu et al. (2019) [6]	86.4 %
Reis et al. (2019) [7]	85 %
Zhou et al. (2019) [8]	92.9 %
Shu et al. (2019) [9]	90.4 %
Proposed Framework	99.68 %

- Model Limitations: there are inherent limitations of the fake news detection models, such as challenges in capturing nuanced contexts, potential false positives or negatives, and sensitivity to certain types of content. Potential model enhancements or alternative approaches should be reviewed to address identified limitations and the trade-offs between model complexity and interpretability.
- Generalization Challenges: these are related to the findings in different contexts, languages, or periods. Address the external validity of your results. For future research to explore the generalizability of the model, such as cross-cultural validation studies, temporal analysis, or investigations into context-specific factors can be evaluated.

Some of the recommendations are as follows.

- User Education and Awareness emphasize the importance of understanding the limitations of automated fake news detection systems and the potential impact of user awareness on system effectiveness. Different strategies for educating users on the capabilities and limitations of the model can help foster a more informed user base.
- Continuous Model Improvement: the dynamic nature of misinformation and the need for continuous model improvement. The benefits of iterative model updates based on user feedback and evolving information landscapes are also advocated for a framework for ongoing model refinement, considering user feedback, emerging trends, and changes in misinformation.
- Collaboration with Fact-Checking Organizations: the role of fact-checking organizations in the fight against misinformation and potential collaborations can help enhance the reliability of the model through fact-checking partnerships, so collaboration with fact-checkers would certainly aid in validating and improving the accuracy of the model's predictions.

Social media platforms could leverage the proposed framework to proactively identify and flag potentially deceptive content, thus reducing the virality of fake news. Government agencies and electoral bodies might consider implementing our framework as part of their disinformation monitoring strategies to safeguard the integrity of elections. In conclusion, this research presents a promising approach to combat fake social media news and distorted campaigns. While there are limitations, the potential benefits for society, democracy, and information integrity are substantial.

8. Conclusion

Fake news has grown in popularity, making fake news research even more vital. As a result, a plethora of fake news detection technologies have emerged, the vast majority of which depend on news content. To overcome this gap, researchers proposed a fake news detection approach to investigate the propagation of fake news on social media, including the content that's being shared, the peddlers, and the connections between the spreaders. As a result, in this study, the authors reviewed observable detection of fake news. The researchers build a paragraph co-attention sub-network that collects check-worthy words and live comments for the detection of fake news using both news information and customer feedback. Extensive experiments on real-world datasets are performed in this research to indicate that the proposed approach not only outperforms but also outperforms most state-of-the-art fake news detection systems. In contrast to other comparable techniques, the authors' analysis of fake news campaigns and their effects uses a machine learning algorithm and produces very accurate findings. 99.68 % accuracy was reported in the results, a much better accuracy than other approaches that produced lower accuracy.

Funding

This research work was supported by the National Research Foundation of Korea (NRF) grant funded by the South Korea government (MSIT) (NRF-2023R1A2C1005950).

Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Akashdeep Bhardwaj: Software, Writing – original draft. **Salil Bharany:** Supervision, Validation. **SeongKi Kim:** Funding acquisition, Methodology, Software, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Akashdeep Bhardwaj and SeongKi Kim equally contributed this work.

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