

## Review Article

# Analyzing Machine Learning Enabled Fake News Detection Techniques for Diversified Datasets

Shubha Mishra <sup>1</sup>, Piyush Shukla <sup>2</sup> and Ratish Agarwal<sup>3</sup>

<sup>1</sup>Information Technology, LNCT, Bhopal, India

<sup>2</sup>DoCSEUIT-RGPV, Bhopal, India

<sup>3</sup>Department of Information Technology, University Institute of Technology, RGPV, Bhopal 462033, India

Correspondence should be addressed to Shubha Mishra; [mis.shubha@gmail.com](mailto:mis.shubha@gmail.com)

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Fake news, or fabric which appeared to be untrue with point of deceiving the open, has developed in ubiquity in current a long time. Spreading this kind of data undermines societal cohesiveness and well by cultivating political division and doubt in government. Since of the sheer volume of news being disseminated through social media, human confirmation has ended up incomprehensible, driving to the improvement and arrangement of robotized strategies for the recognizable proof of wrong news. Fake news publishers use a variety of stylistic techniques to boost the popularity of their works, one of which is to arouse the readers' emotions. Due to this, text analytics' sentiment analysis, which determines the polarity and intensity of feelings conveyed in a text, is now being utilized in false news detection methods, as either the system's foundation or as a supplementary component. This assessment analyzes the full explanation of false news identification. The study also emphasizes characteristics, features, taxonomy, different sorts of data in the news, categories of false news, and detection approaches for spotting fake news. This research recognized fake news using the probabilistic latent semantic analysis approach. In particular, the research describes the fundamental theory of the related work to provide a deep comparative analysis of various literature works that has contributed to this topic. Besides this, a comparison of different machine learning and deep learning techniques is done to assess the performance for fake news detection. For this purpose, three datasets have been used.

## 1. Introduction

Fake news detection (FND) has recently picked the attention of a large number of academics, with many sociological studies demonstrating the effect of fake news and how people respond to it. To describe fake news as any material capable of making readers believe in information that is not real, one must first define what false news is [1]. Spreading false news widely harms society and the person. Initially, this kind of false news has the potential to change or destroy the authenticity balance in the news ecosystem. Because of the features of fake news, people are coerced into accepting incorrect or skewed ideas they would otherwise reject [2]. Political messages or influence

is often communicated via the use of false news and propagandists [3]. Fake news has a lasting impact on how people interact with and react to genuine news this. To reduce the harmful impacts of false news, it is critical to develop a system that can automatically detect it when it appears on social media [4]. However, there are several difficult research issues with fake news detection on different social platforms. A variety of research objectives observed in this regard includes the identification of the source of origin or uploading of the particular news or data on the social network, to understand the actual intention or meaning of the data uploaded and to determine the extent of authenticity and validate it to make decision so as to consider it as genuine or fake. The peculiarities of news

make automated fake news detection a difficult task. To begin with, readers are duped by false news, making it impossible to tell the difference between real and fraudulent information [5].

When it comes to fake news, there is a wide range of formats and subjects to choose from. These false reports attempted to distort the facts by using various language approaches [6]. Existing knowledge bases fail to validate false news effectively when it is linked to time-critical events because there are not enough supporting claims or facts to back them up [7]. The data (i.e., unstructured, noisy, unfinished, and large data) generated by false news is also on social media [8]. Researchers have attempted in recent years to uncover problems with false news, their trustworthiness on social media, especially Twitter, YouTube, Facebook, and television [9]. Data are used to evaluate political/product views, user emotions, natural phenomena in process, global events, and satisfaction with health care service consumers [10]. Due to these network interactions, it is possible to extract valuable post features while also taking advantage of the network's interactions. Fake news has characteristics, kinds, and detection methods, and all of which are discussed in this study. Further research on fake news detection apps will be guided by appropriate explanations regarding false news. The benefits and limits of conventional fake news detection are addressed, as well as the difficulties posed by false news on social media. However, there are several problems with the fake news detection social media presence that need additional study. This analysis will ultimately help in the selection of appropriate techniques to be applied for identification of the fake data from the corresponding real time social media dataset globally and will make the users well aware while sharing information and communicating during using variety of social media platforms.

*1.1. Need and Motivation.* There is a vital need to deal with the fake data spread across online platforms since it creates hassles for users in terms of rumors, identity theft, lack of authenticity and confidentiality, fake profiles etc. The dissemination of false information through social media as possible undermines trust in the news ecosystem, harms the reputations of individuals and organizations, and causes fear in the public at large, all of which have the potential to undermine societal stability. False news that has been generated is very difficult to spot since the terminology used in the news is comparable to that used in real news, and fake news is produced with the goal of instilling confidence in the public. As a result, false news identification is required.

*1.2. Challenges.* The most difficult aspect of detecting false news is determining whether or not a bit of information is based on factual facts. A fact is merely a fundamental notion made up of anything that has occurred at some point in the past, someplace, and eventually with or to someone. Recognizing the importance of information does not appear to be something computers should be able to accomplish easily if they are given total control over what information is delivered to whom, when, and through what channel. This is important as numerous social media posts follow the fundamental idea of describing something. So it is necessary to collect the journalistic criteria core.

## 2. Fake News Detection

*2.1. Definition.* Fake news is deliberately written misleading material meant to deceive the public. Authenticity and purpose are the two most important aspects of this concept. Fake news has two characteristics: firstly, it contains incorrect material that could be confirmed as such, but secondly, it is produced with the dishonest goal of misleading readers. The distribution of false material through social media may have important implications, such as weakening public faith in the news ecosystem, hurting an individual's or organization's reputation, or causing fear among the general public, all of which can affect society's stability. The data may be represented as a collection of tuples consisting of headlines and text from a certain number of news articles, with  $A = \{(A^H, A^T)\}$ . It determines not whether a piece of info is fake in the fake news identification issue [11].

The methods used to manipulate information differentiate real news from fake news. Alternatively, news material may use deceptive tactics such as fabricating facts to make the customer believe something they do not want to believe. It is also possible to impose material that seems to be from reputable sources, but the sources are not. Additionally, fraudulent features of fake news include the use of altered material, such as headlines and pictures that do not match the information delivered or the contextualization of fake news using real components and information but in a misleading context (Table 1).

*2.2. Types.* Fake news detection may be split into three categories as follows:

- (a) Fabrication: fabricated news is a deliberate omission of information that typically only comes from a single source. The source is likely aware of the story's inaccuracy. Clickbait is critical to the success of fake news stories
- (b) Hoax: this kind of reporting employs more complex deception techniques to mislead the public. Multiple outlets disseminate fake news. It is possible that some people consider the tale to be real. This kind of news may be found on a variety of sites, such as the fake news about Donald Trump that circulated throughout the election on different social media platforms, including Twitter, Facebook, and blogs, so the general public is more likely to believe it
- (c) Satire: faked news that is presented as humorous by the source. In the case of sharing satire with individuals who are not acquainted with the material's origins. Some people may mistakenly believe it to be true

*2.3. Approaches.* The following are the results of a false news detection study carried out by a variety of researchers using a variety of approaches:

- (a) Knowledge-based: approaches based on knowledge, such as fact-checking in news reports with the assistance of additional sources owing to fact-checking, an article's statements may ascribe a correct value

TABLE 1: Seven types of fake news [12].

S. no.	Type	Details
1.	False connection	If the information is not supported by the headlines, images, or captions.
2.	False context	If authentic material is accompanied by erroneous metadata.
3.	Manipulated content	Real info or images that has been tampered with to mislead the public.
4.	Satire	No malicious purpose, yet it has the ability to deceive.
5.	*Misleading content	Using information to help clarify a problem.
6.	Imposter content	If real sources are impersonated.
7.	Fabricated content	New material which is blatantly misleading and intended to hurt people.

in light of the mitigating circumstances. Approaches to fact-checking may be divided into three types: expert-driven, crowd sourcing-driven, and computationally-driven

- (b) *Style-based*: based on the writing style, style-based methods identify false news. For the most part, there are two major types of style-based methods: one that is deception-oriented and the other of which is objectivity-oriented. Deception-oriented is concerned with assertions or claims in news material that are false or misleading. Approaches that focus on objectivity look for style cues that suggest that news reporting have skewed toward sensationalism and bias
- (c) *Stance-based*: stance-based methods leverage customers' views from appropriate post contents to verify the authenticity of the actual news reports. When representing the stance of customers, one has the option of using explicit or implicit methods. Approaches based on stance in a social setting
- (d) *Propagation-based*: based on propagation, these methods looked at how misinformation propagated on social media and the relationships between postings to estimate news credibility. Approaches focused on propagation in a social environment [13]

### 3. Fake News, Deception, and Clickbait Characteristics

Examining the findings of several research shows that false news, deceit, and click bait all have their unique features.

*3.1. Fake News.* For the most part, the existing study concentrates on analyzing the trends and characteristics of fake news distribution in contrast to the dissemination of correct info. From 2006 to 2017, Vosoughi et al. looked and examined how accurate and false news articles spread on Twitter, with the data coming from 126 K stories shared by 3 M individuals and tweeted over 4.5 M times. Fake news spreads quicker, further, and to a wider audience than reality does, according to the authors. False news stories on terrorism, natural catastrophes, science, urban legends, and financial information had less of these impacts than do stories about fake political news, according to the researchers. In a recent study, Shubha Mishra found that those who disseminate

false news had a denser social network than people who spread real news [14].

*3.2. Deception.* Disinformation (deception) is the dissemination of incorrect information on purpose. Most studies use the term "fake" or "deceptive" statements and reasons to describe different types of deception. Psychological and social science ideas have shown certain language signals that indicate whether someone is telling truth or lying [5]. This hypothesis asserts that statements of fact vary from fantasy ones in information fashion and quality; fact tracking demonstrates that real events have greater levels of sensory info. The four-factor theory stated that untruths are explained separately in words of feelings or cognitive processes than truth, or the info modification theorist validates that extreme data quantities commonly occur.

*3.3. Clickbait.* Clickbait headlines are those written with the express aim of luring readers in and enticing them to follow an association to a certain Web page. Such clickbait is as follows: "33 Heartbreaking Photos Taken Just Earlier Death," People are saying, "You won't trust what Obama did!" The worst has happened: Hillary's ISIS emails have been leaked, and it is worse than anybody imagined. Clickbait authors go to tremendous pain to establish an information gap between their headlines and the understanding of the ordinary reader to accomplish their purpose. When there are knowledge gaps, people experience a sense of curiosity, which drives them to seek out the information they are lacking to alleviate this sensation.

### 4. Features for Fake News Detection

Numerous studies have used feature-based classification to better identify false news stories. False information may be detected with ease using textual characteristics. The following sections go through a few of the features [15].

- (a) *Semantic features*: semantic features capture the semantic (meaning) aspect of the text. These features derive a meaningful pattern from the data
- (b) *Lexical features*: lexical features are mainly used in tf-idf vectorization for summarizing the total number of unique words and the frequency of the word. Lexical features include pronouns, verbs, hash tags, and punctuation

- (c) Sentence-level features: these features include a bag-of-word approach, part-of-speech, and n-gram approach. Sentence level features are the language feature which is mostly used in text classification
- (d) Psycholinguistic features: these features and word count is based on dictionary-based text mining software

## 5. Taxonomy of Fake News Detection

Fake news is exposed to use a variety of detecting methods drawn from different networks and databases. First, a breakdown of the different networks is provided:

*5.1. Platforms.* Carrier platforms are used to offer fresh material to end consumers, and a list of the most prominent carriers is given in this section. The most popular operating systems are shown as follows:

- (a) Standalone website: any website can submit new tales, and everyone will have its URL. These URLs are being used directly by users if they wish to share or publish a social media post. Most websites fall into one of the three categories: blogs, media, or prominent news websites. Famous new sites, with their very own social media presence, are the ones that provide genuine material. Blog sites, that heavily rely on user-generated material and unsupervised content, are prime locations for spreading misinformation. In accordance with media-rich content, media sites enable customers to create their websites by creating material depending on style and customer interests
- (b) Social media: a most popular method for disseminating the information on these websites is via the spreading of it. A daily news source is shared by almost 70% of its consumers. Consumers distribute the data using the most popular social networking platforms, like Twitter, Facebook, and WhatsApp. You may reach a bigger audience using false information if you produce sponsored advertisements for every Facebook post in which users submit messages of restricted character length and then distribute them with the other Twitter users by tweeting them back to them
- (c) Emails: users trust email as a reliable medium for receiving news; however, verifying the legitimacy of news emails is a difficult problem
- (d) Broadcast networks (Podcast): just a tiny percentage of people use podcasting for anything other than news, making it a specialized subset of sound multimedia
- (e) Radio service: the verification of sound veracity is a significant challenge for radio services since these services are efficient news sources for the community

## 6. Different Types of Data in News

The novel story is constructed using a variety of various kinds of data, all of which are explored in the next section. Consumers often consume news in one of four forms, which are detailed in the following:

- (a) Text: language is being utilized to examine the content of a string of text, with particular attention paid to text as a means of interaction. Grammatical, tone, and pragmatics are all used in discourse analysis since language is more than just words and phrases
- (b) Multimedia: it is possible to use music, picture, video, and graphics together in a single project since multimedia is used. Because of its visual depiction, it immediately grabs the attention of an audience
- (c) Embedded content or hyperlinks: it is possible for users to connect off to different sources by using hypertext links, and the premise of a news article is utilized to win readers' confidence. Authors use the advent of social media to incorporate a snapshot of important social media postings like a tweet, a sound cloud clip, a Facebook post, a YouTube video, and so on
- (d) Audio: the audio is one of a component of the multimedia category; it is a stand-alone medium for news sources. This medium, which includes different media like radio services, podcasts, and broadcast networks, is used to transmit news to a larger audience

## 7. Types of Fake News

Researchers in the social sciences examine fake news from a variety of angles before coming up with a broad classification of different kinds of fake news. This classification was given in the following statement:

- (a) Visual-based: the types of fake news are described in the material using a graphical depiction of video or photo shopped pictures or a mix of both [10]
- (b) User-based: using this method, the intended audience could be attracted by establishing fictitious accounts that reflect certain demographics such as gender, age, and culture [16]
- (c) Post-based: social media sites like Facebook posts with video or picture captions, memes, tweets, and so on are the common places for this kind of fake news to emerge [17]
- (d) Network-based: there are some people of an organization who are linked to this type of fake news, where this concept is primarily used to groups of linked persons on LinkedIn and friends-of-friends on Facebook [18]
- (e) Knowledge-based: these new articles will be created using articles that provide plausible explanations or

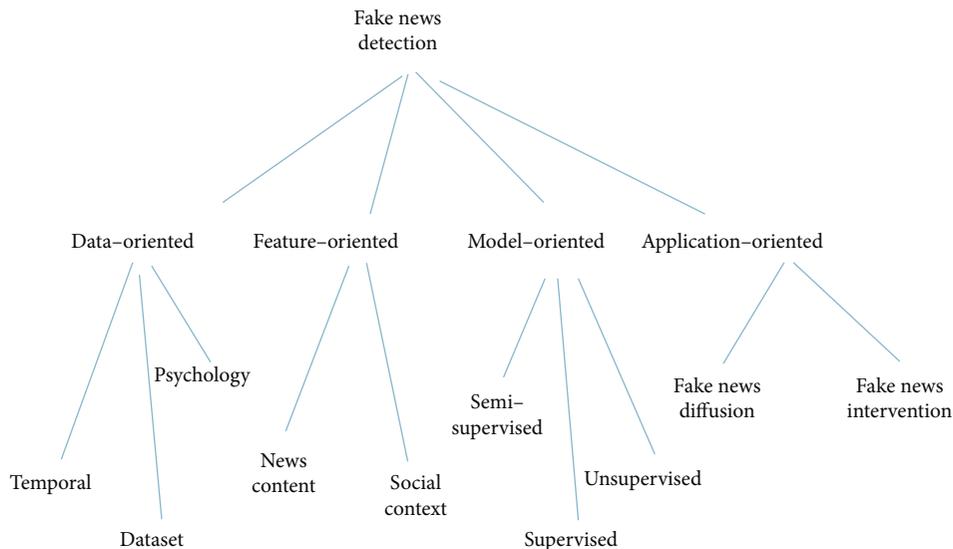


FIGURE 1: Numerous techniques to recognize fake news (Source: <https://www.kdnuggets>).

scientific knowledge about an unsolved problem to disseminate false info [19]

- (f) Style-based: false news may be produced by anybody with the ability to write in a variety of styles, but this style-based news was only concerned with how the false info was presented to end consumers [20]

Some ways for determining whether or not a piece of news is false are shown in the Figure 1 or the techniques described below.

### 8. Detection Methods for Identifying Fake News

There are many current methods created depending on feature extraction for characterizing false news and also different kinds of news data in the preceding section. The next paragraphs describe several feature-based approaches.

*8.1. Linguistic Feature-Based Methods.* Mishra et al. [21] utilizing linguistic-based methods, the essential language characteristics may be gleaned. In addition to syntax and grams, there are a variety of other characteristics like punctuation and readability, with the most significant of these being represented as follows:

- (ii) n-grams: for the purpose of finding unigrams and bigrams in a narrative, writers gather words. TFIDF (term frequency inverse document frequency) is used to save and retrieve the extracted characteristics
- (iii) Punctuation: the FND methods use punctuation to show the distinction between honest and fraudulent texts
- (iiii) Syntax: context-free grammar (CFG) states that this approach extracts several characteristics. In line with the lexicalized production rules, which

are a mix of parent and grandparent nodes, this collection of characteristics is put into practice

*8.2. Deception Modeling-Based Methods.* When it comes to grouping true vs misleading tales, two theoretical methods come into play: vector space modeling (VSM) and Rhetorical Structure Theory (RST). Each text in a hierarchical tree can be analyzed utilizing RST to uncover rhetorical connections. The VSM is used to identify the RS relations' outcomes, and that is all. RST-VSM technique offers curating data edge depending on the distance among samples as contrasted using similarity-based cluster analysis [22].

*8.3. Clustering-Based Methods.* Using the Graphical Clustering Toolkit clustering package, writers have utilized clustering to assist distinguish among reports that employ the same clustering methodology [23]. When utilizing this technique, a large no. of sets are processed, and a limited number of clusters are formed/sorted employing hierarchical clustering and k-nearest neighbor technique, grouping comparable news items depending on a normalized frequency of connections.

To determine if a new narrative is deceptive, researchers use the concept of computed coordinate distances. It appears that this technique, depending on the author's assertion of a success rate of 63 percent, is particularly effective on big datasets. There is a chance that if this method is used on current false news, it may not offer reliable results since comparable news story sets may not be accessible, i.e., similar data may not be accessible [24].

*8.4. Nontext Cue-Based Methods.* The nontext substance of news is utilized to persuade readers to place their trust in tainted information, which is the primary goal of this method. Several analyses are employed here, including two which are classified as:

- (i) Image analysis: by employing a well-known key technique, or strategic use of pictures, the aim is to influence viewers' emotions
- (ii) User behavior analysis: a content-independent technique known as user behavior analysis is used to evaluate reader behavior (e.g., how they interacted with news). The method's primary goal is to better understand social media customer behavior and the pictures they post as teasers

8.5. *Content Cue-Based Methods.* Mishra et al. [25] this technique will be created in accordance with the ideologies of news readers' choices and the manner in which journalists write the news for them as readers. There are many different methods to write these news articles, but they all use the same basic information. This technique presents 2 distinct analyses, as described in the following:

- (i) Lexical and semantic level of analysis: as a result of the author's use of persuasive language, readers would take the false news as fact as in a narrative. The stylistic characteristics of text may be extracted utilizing automated techniques to tell between two journalistic genres
- (ii) Syntactic and pragmatic level analysis: the pragmatic function is used in the discourse to identify the reference for future sections. By creating catchy titles, you may ensure that messages are full of meaningless rambling

## 9. Probabilistic Latent Semantic Analysis

LSA, a well-known method for answering some of these questions, is used here. We want to reduce the size of text document vectors by mapping them to something smaller termed latent semantic space. This can be done by using vector space descriptions of text documents. A key aim of LSA, as the name implies, is finding a data mapping that goes well outside the level of vocabulary to uncover semantic relationships between items of interest. As a result of its broad applicability, LSA has proved to be a useful analytical tool. Even yet, its theoretical underpinnings are woefully inadequate and unfinished [26]. Dimensionality reduction is accomplished using an algebraic technique known as LSA. The LSA translates document vectors from the keywords space to a low-dimensional space comprised of semantic dimensions in low-dimensional space. Semantic dimensions make up a considerably smaller portion of the overall no. of words. Compared to the original space, where documents (vectors) are sparsely dispersed and most of their coordinates are zero, the converted space is considerably dense. The LSA selects a projection with the greatest possible variation in the data along the axes it will be used on. In a new environment, two papers that first have few or no common words may seem very related.

As a new statistical method, probabilistic latent semantic study (PLSA) uses two-mode, as well as cooccurrence data for the analysis, and has uses in info retrieval and filtration, NLP, text mining, and related fields [26]. The PLSA, as

opposed to conventional LSA, specifies a suitable generative data model for the analysis of PLSA data. This has several benefits: This means that conventional statistical methods for model fitting and model selection, including complexity management, may be used on a broad scale. A PLSA model's prediction accuracy, for illustration, may be evaluated using a cross-validation to determine its quality. Every time a word appears, PLSA assigns a latent context variable to it, taking polysemy into consideration directly. Hofmann, (1999), polysemy and synonymy in the text are captured using a probabilistic architecture in PLSA, which may be used for applications including such retrieval and segmentation. The cooccurrence information is modeled using a mixed decomposition, and the probability of words and documents are calculated using a convex mixture of different features. The probability distribution of the mixed approximations is clearly defined, and the aspects have a clear probabilistic meaning in terms of combination component distributions. According to this prototype, the probabilities of the observed data will be as high as possible by choosing model parameter values that maximize the chance of those probabilities being true. It is a common practice to use the expectation-maximization (EM) technique to estimate probabilities with high accuracy [27]. This means that the quality of a solution is determined by the model's initialization, not the other way around. Furthermore, as we will see, the probability values obtained from various initializations do not match up. There is no way to compare predictive accuracy across various models using the likelihood function calculated on the training data. A better approach would be to discover a method to initialize the PLSA model than to attempt to guess which model would perform better from a collection of models. A methodology for better initializing the parameters of a matching PLSA model will be shown by the use of an LSA technique. After that, the original estimate is fine-tuned with the help of the EM algorithm. These two approaches are combine to maximize the benefits of both [27]. When it comes to the study of two-model and cooccurrence data, PLSA is one of the most common statistical methods available. It has uses in the fields of feature extraction and filtering, natural language processing, ML from text, and other associated fields. In practice, unfortunately, PLSA was hardly used on big datasets owing to its computational complexity and time consumption [28].

The PLSA is a method that falls under the latent semantic category. To determine the underlying semantic representation of the model, it is essential to represent cooccurrence data in a probabilistic framework. PLSA may be seen in two distinct yet complementary ways [29]:

- (i) Latent variable model: the aspect model, which is a statistical model, serves as the foundation for the probabilistic framework of PLSA. Concerning the text domain, the latent/hidden variables (expressed by topics/concepts) are linked with the observable variables (indicated by documents and words, respectively)
- (ii) Matrix factorization: the PLSA, like Latent Semantic Indexing (LSI), attempts to factorize the sparse

cooccurrence matrix to decrease the dimension of the matrix. Though the probabilistic explanation of PLSA is generally considered superior, the LSI approach accomplishes factorization only via the use of mathematical underpinnings (more specifically, LSI employs the singular value decomposition method), which is generally considered to be less sound

## 10. Machine Learning

Machine learning [30] is unquestionably one of the most important and effective technologies available today. Artificial intelligence has a subset known as ML. To put it another way, the term “ML,” developed by American computer games and artificial intelligence pioneer Arthur Samuel in 1959, means “allowing computers to learn without expressly being instructed.”

ML is a branch of computer science that is distinct from more traditional approaches. Algorithms are a set of instructions designed to help computers analyze and solve issues. ML techniques, on the other hand, allow computers to learn from input data via descriptive statistics as well as production values within a defined range. Therefore, ML makes it easier for computers to build models data from sample data and also accelerates decision-making processes based on real-world inputs.

For software programs to predict incoming data trends and relationships more successfully without explicitly programming the outcomes and change them accordingly, ML involves several methods.

There are many applications for ML in a broad range of fields, including the following:

- (i) Prediction: using ML techniques in prediction systems, weather forecasts, and wrong-result probabilities analysis is possible
- (ii) Computer vision: image processing may make use of ML techniques
- (iii) Speech recognition: to translate text to speech, use ML techniques, or operate autonomous vehicles and robots via voice instructions and voice recognition
- (iv) Health diagnoses: medical conditions may be predicted using ML algorithms

*10.1. ML Methods.* In ML, analyses are often grouped into broad categories for ease of reference. To categorize things, we looked at how machines learn and use feedback. Supervised learning, which uses human-labeled data and information to train algorithms, and unsupervised learning, which provides no clear examples of a technique and requests that meaning be discovered in its input data, are the most commonly used methods in ML [31].

*10.2. Random Forest.* Regression and classification problems may both benefit from the random forest approach. It is a method of supervised categorization that results in a dense forest. It seems more studied the more trees there are in the forest as a whole. It is also possible to say that the greater

the number of trees in a forest, the more accurate the results will be. There are many benefits of using RF algorithms. The classifier can deal with omitted values. The RF classifier may be simulated for categorical variables as well. Over fitting problems never occur when using the random forest method for classification tasks [32].

*10.2.1. K-Nearest Neighbors.* KNN is a simple algorithm for categorizing new cases based on how similar existing ones are. The KNN was used to identify trends and patterns in statistical data. An instance ( $x$ ) is predicted by KNN by scanning the whole training program for most similar examples and summarizing result variables for those  $k$  cases [33].

*10.2.2. Logistic Regression.* It is a statistical analysis technique known as logistic regression that predicts a knowing value based on previous observations from a knowledge collection. The method makes it possible for an ML application to categorize incoming data based on previous training data using an algorithm. The algorithm’s ability to anticipate classes within datasets should improve when more relevant data is received. As part of the extract, transform load (ETL) process, logistic regression allows datasets to be placed into specified buckets so that knowledge may be staged for study. In a logistic regression model, one or more existing independent variables are analyzed to see how they relate to a dependent data variable.

*10.2.3. Support Vector Machine.* To categorizing data, a method known as a support vector machine uses supervised learning to sort it. Because it is previously been trained, it uses a set of data, that is, already been divided into two groups when creating the model. It is the job of an SVM algorithm to figure out where a new piece of data fits in the scheme of things. As a result, the SVM may be considered a nonlinear linear classifier. Data is analyzed for classification and multivariate analysis using an SVM, a machine learning method. There are a variety of applications for SVMs inside the sciences, such as text classification and picture classification, including handwriting recognition.

*10.2.4. Naïve Bayes.* A probability-based classification method predicts class membership based on the likelihood of all possible characteristics being present in a sample at a given time. If the decision of the target class is influenced by a combination of several characteristics known as evidence, this method is used. It is possible for NB to examine characteristics that will have little influence if taken individually, but when taken together may have a substantial effect on the likelihood of an instance belonging to a certain class. Assuming all features are equal, the value of one feature does not influence the value of another feature. As a result, the functions are distinct. To compare more complicated methods, it may be used as a starting point for incremental learning, in which the model is updated using fresh example data rather than having to start from the beginning with a whole new model.

*10.2.5. Decision Trees.* The decision tree is an example of a supervised learning model. We can use it for classification

and regression since it is a powerful nonparametric approach. The source set is divided into subsets in a decision tree depending on the results of an attribute value test. Every subset is divided recursively, and the procedure is repeated. When all of the nodes in a subset have the same variable, the recursion is over. The decision tree's nodes and leaves are the outcome. In a decision node, the leaf node indicates either categorization or decision. It is capable of dealing with both category and statistical data.

## 11. Deep Learning

Deep learning is a subtype of ML that solves complex problems by processing in the same way the human brain does. For this reason, Islam et al. [34] modern society, is using deep learning methods, which can solve text recognition problems like identifying fake news and spam by providing a high degree of characteristics on their own. Fake news identification using deep learning methods has a lot of potentials. In Alekya et al. [35], only a few researches indicate that neural networks are important in this field. Dechter with artificial neural networks predicated on a Boolean threshold was the first to use the term deep learning (DL) in the machine learning field. As part of artificial intelligence research, deep learning (DL) is an important approach, that is, being used in an extensive range of apps, from computer vision to speech identification to natural language processing to anomaly detection to asset allocation to healthcare monitoring to personality mining. It is now being utilized more and more to help make decisions by analyzing data and finding patterns. Nasir et al. [36] also helps to enhance learning execution, extend the study field, and streamline the measurement process thanks to this cutting-edge approach. Various methods have been suggested over the last several decades to address numerous online social network issues (false news, disinformation, anomaly detection, etc.). For the most part, researchers are always looking for new areas of investigation to fill in research shortages. More than one network like recurrent neural networks (RNN), long short-term memory (LSTM), and CNN are introduced to help other obtain information and knowledge from various implementations, and deep learning is one such technology that has become extremely prevalent [37].

*11.1. Deep Neural Networks (DNNs).* DNNs have been suggested as a pattern recognition system that mimics human brains. The DNN is a neural network with a single hidden layer with input, output, and output layers. It turns on or off the input/output relationship using mathematical techniques. There are no loops in this feed-forward network; thus, data moves directly from input to output. The back-propagation method is used to teach them.

*11.2. Convolutional Neural Networks.* CNN utilizes matrix multiplication to generate outputs for use in subsequent training. Convolution is the term used to describe this technique. As a result, convolution neural networks are the name given to this particular kind of neural network. Word vectors are used in natural language processing (NLP) to represent

sentences and news articles. After that, a CNN is trained with the word vectors. Specification of the kernel, as well as filter sizes, allows for training to be done. A CNN is capable of having many dimensions. The CNN is a network of neurons linked in layers that takes inputs and outsources the output. CNN is used to accept inputs and generate output. CNN is an object identification as well as image analysis feed-forward network paradigm. There are three layers in a neural network: a convlayer, a detector layer, and a pooling layer. The convolution layer's task is to create a map with convoluted features, as described above. There are nonlinear components in feature maps that are noticeable, such as those seen in the detector layer. The predecessor information is reduced as well as the output is provided by the pooling layer. CNN looks for the slumbering people in the storylines. The data size and training data are the main uses of this model. The performance and speed of the CNN model are properly considered.

*11.3. Recurrent Neural Networks (RNN).* For learning, RNN utilizes sequential data processing. Sequential processing is justified by the fact that it can keep track of what occurred before it. The output from the one-time step is used as input for the following time step; hence, the name "recurrent." This is accomplished by storing the results of the preceding time step in a temporary variable. Thus, we are able to discover patterns in the training data that are dependent on one another over time. Back propagation is used to train the RNN model. ANN models, like this one, are a subset of them. As a feed-forward network, it utilizes recurrent loops as input. Sentiment analysis, voice recognition, and other tasks use RNN to analyze data sequentially. Models using RNN have more memory and takes prior model inputs into account. This model is capable of understanding and responding to human language. Both Siri on Apple's iPhone and Amazon's Echo show us how RNNs may be used. It is impossible to make predictions based on the past. To outsource the output, it keeps track of previous inputs and utilizes the same settings for them. Several applications rely on embedded architecture in the data sequence for valuable knowledge, and RNN makes advantage of such embedded structure by using RNN. The RNN has the benefit of greater contextual information collection.

*11.4. LSTM.* These LSTM cells, which are a kind of recurrent neuron that has been shown to provide extremely intriguing results in sequence modeling issues because they can "remember" information from the past, constitute the basis of this design. They can avoid the vanishing gradient issue by using LSTM units, which are made up of several gates that are responsible for keeping track of a hidden cell state. This enables LSTM units to recall information from farther in the past than vanilla recurrent units. Since words from the past frequently affect the present, this is an essential element in NLP. There are two LSTM layers in the architectural history: one for forward and one for the backward data feed. We made this choice because we believe that words in the future often change the meaning of words in the present. Polysemous terms like bank, mouse, and book, for example,

demonstrate the need for context while attempting to mimic their meaning.

*11.5. Artificial Neural Networks.* The ANN algorithm is a computer program. Nonlinear and complicated patterns were used to mimic topological systems. ANNs are employed in satellite image categorization. An ANN resembles a human neuron in many ways. This results in the transmission of electrical impulses and makes use of a large number of linked processing units. Input, output, and hidden layers make up this feed-forward model. To accept information and communicate with the hidden layer, the input layer's function is to act as a conduit. As a result, the answer from the hidden layer is sent to the output layer after being combined with the input layer. To compare the real output with the ANN output, we feed the neural network with various inputs or outputs.

*11.6. Restricted Boltzmann Machine (RBM).* A generative stochastic ANN, or RBM, is a kind of neural network. A possibility spreading over the set of inputs may be learned by it. General Boltzmann machines do not support learning; however, a variant known as the limited Boltzmann machine does. Therefore, connections between concealed units within a layer are not permitted. By stacking RBMs in this manner, numerous hidden units may be effectively trained. For example, we used RBMs to extract spam detection characteristics autonomously.

*11.7. Deep Boltzmann Machine (DBM).* There are many hidden random variables in a DBM, which is why it is called a binary pair-wise Markov random area. Malicious actions may be detected via a network of symmetrically coupled stochastic binary units (SBUs). As an instance, Jindal et al. utilized a multimodal benchmark dataset to identify false news. To identify spoken questions, they used a DBM-based multimodal DL model built using Deep Boltzmann Machines (DBMs). Layers are linked, although units within each layer are not.

*11.8. Generative Adversarial Network (GAN).* GANs are a kind of machine learning system. This method learns from a training set and then generates fresh data with similar statistics as the training set. According to previous research, the most common cause of widespread rumors is the intentional distribution of information intended to create agreement about rumor-related news events and developed a generative adversarial network model to improve the robustness and efficiency of automated rumor identification and to discover strong characteristics associated with unclear or contradictory voice output and rumors.

## 12. Literature Review

In this paper, Sansonetti et al. [38] presented a thorough study of the characteristics that, both automatically and manually, are more predictive for the detection of social network accounts responsible for propagating false news in the online environment. As a result, Twitter characteristics like social and personal info, as well as engagement with material and other customers, are the info collected from the observed indi-

viduals. This was followed by an offline study done using deep learning methods and a real-time online analysis involving actual users to classify trustworthy and unreliable user profiles. The findings of the experiments, which have been statistically verified, indicate which information helps computers and humans identify malevolent users.

The research by Antoun et al. [39] provides the most advanced techniques for detecting false news in tweets, including methods for identifying domains and bots. One of the suggested solutions took first place in a fake news competition held recently on an international scale. Detection of false news requires models, and here, they provide two. When it comes to competition, the winning model incorporates similarities between the embeddings of article titles and the top five matching Google search results. Using the advancements in Natural Language Understanding (NLU) deep learning prototypes, the new model can distinguish between authentic and fake news items based on variations in their stylistic approaches to authoring. This new model, which was created after the competition ended, beats the previous model by a significant margin. There is a hybrid method that uses named entity characteristics along with semantic embeddings generated from end-to-end models to identify news domains. Many characteristics may be used to identify a Twitter bot, including time elapsed between when an account was set up and when the tweet was sent, the existence of a tweet link, the user's current location, and metadata associated with the tweet. Some experiments shed light on the relative significance of various characteristics, and the findings show that all suggested models are preferable in terms of their performance.

The goal of this study is to correctly recognize the news stance and [40] present a technique based on a pretrained BERT language prototype. While some earlier studies relied on the knowledge of just one inference direction for categorizing the posture, this may have left out critical information. Since bidirectional perspective information may be used to categorize the posture more thoroughly, their model utilizes bidirectional inference to find the correct pose. Aside from that, they classify the stance identification task as a hierarchical structure task that incorporates subject information to aid in classifying the user's position. The results of our experiments indicate that our model is more accurate in determining a person's stance.

These researchers [41] developed a semisupervised learning algorithm to identify false news on social media before it spreads to the wider public. They can cope with the enormous quantity of unlabeled data on social media by utilizing a semisupervised learning approach. To begin, they created a prototype to extract customers' comments and then used the CredRank method to determine the trustworthiness of those users. Finally, they created a tiny network of people who were actively spreading a particular piece of news. Their news classifier SSLNews uses the results from these three stages as inputs. One shared CNN network, one unsupervised CNN network, and one supervised network comprise SSLNews. To test Politifact and Gossipcop, they utilized data from the actual world. The SSLNews achieves a precision of 72.25% on Politifact and 70.35% on Gossipcop while utilizing 25%

TABLE 2: Comparison table of different fake news detection methods.

Authors (year)	Aim	Issues	Methods	Datasets	Findings	Shortcomings/future work
Sansonetti et al. [38]	Detecting fake news and unreliable users	Figuring out whether or not a piece of social media news is trustworthy by looking for trustworthy sources	Deep learning techniques, CNN, LSTM, and neural network classifier	Twitter (user-profiles and shared news)	Recognizing reliable profile. Check for distributed material and social information's trustworthiness. The average accuracy of 90%.	Can be used of new datasets of news and users with further reliability prediction features.
Antoun et al. [39]	To address the risk for fake news spreading	Detecting fake news, identifying domains, and identifying bots in tweets	Bi-LSTM and voting classifier	QICC contest dataset	Superior performances and high impact features	Enhancing the detection of fake news by using elements from fact-checking sites in addition to Google searches.
Lin et al. [40]	To properly determine the position of news	Only one inference direction was utilized for categorizing the stance, which may have resulted in some crucial info being lost	BERT language model	Fake news challenge stage 1(FNC-1)	Detect the stance more accurately	The misprediction example of the proposed model is the stance relation of claim and article is "disagree" class.
Konkobo <i>et al.</i> [41]	The massive quantity of unlabeled social media must be dealt with	Unwilling to cope with fake news' massive quantity of unlabeled data	CredRank algorithm, CNN	Politifact and GossipCop	Politifact's precision is 71.10 percent, whereas Gossipcop's accuracy is 68.07 percent	There will be improvements to a greater number of prototypes that have been suggested. We will create a multilingual dataset and look at how different languages affect news categorization.
Huang and Chen [42]	So that fake news may be detected with greater precision	Cross-domain intractability issue, the required information is often unavailable or inadequate at the early stage	LSTM, depth LSTM, LIWC CNN, and N-gram CNN	FOR dataset, Buzzfeed corpus, SFL dataset, FND dataset satire, and political dataset	Increase the precision, optimize the weights, and look at the intractability problem cross domains	The grammatical analysis would be investigated in-depth, and the preprocessing will extract more useful info, resulting in improved precision in detecting fake news.
Yanagi et al. [43]	So that others may provide remarks and assist classify documents to assess	Early detection of fake news	Neural network model	FakeNewsNet dataset	Achieved the best recall score	Creating remarks may assist fact-checkers in determining if something is genuine or not.

TABLE 2: Continued.

Authors (year)	Aim	Issues	Methods	Datasets	Findings	Shortcomings/future work
Paixão et al. [44]	To the identification of news depending on several kinds of characteristics	Automatic detection of false news	Supervised and unsupervised learning	Fake.Br corpus	Acquired F1 scores up to 96%	Topic modeling.
Song et al. [45]	To recognize characteristics of fake news	Maintaining the modality-specific characteristics has an impact on the model's performances	Multichannel convolutional neural networks with residual cross-modal attention	Four real-world datasets	Learns more discriminable feature representations	—
Ren and Zhang [46]	To learn the node description in HIN	Intentional rumors may conceal a writing style that has not been well modeled and used to match the additional and distracting multimodal info	Hierarchical graph attention network	Two real-world fake news datasets	Expandability and generalizability	Other node classification related applications.
Ying et al. [47]	To make use of the relationship between segments at the same time	Falsification of multimedia data is a problem that is hardly handled.	Multimodal topic memory network (MTMN)	WEIBO and PHEME	Best performance	Discover innovative ways to utilize deep neural networks' prior knowledge for detecting fake news and other valuable complementary info.
Meel and Vishwakarma [48]	To create and falsify news stories that include both text and graphic elements to check error level analysis	As a result of its capability to have catastrophic effects by focusing on a particular kind of news, social networking became a significant issue.	Hierarchical attention network, bidirectional GRU, and ensemble learning	All Data <sup>1</sup> , fake news Sample <sup>2</sup> , and fake news detection <sup>3</sup>	The dataset's best precision was 95.90 percent while using fake news samples	Fake news identification utilizing multimodal data is still a challenging and unknown area that needs further study.
Khan et al. [49]	The effectiveness of several machine learning techniques on three distinct datasets will be evaluated	Maintaining the modality-specific characteristics has an impact on the model's performances	Pretrained language models, deep learning, and machine learning approaches	Liar <sup>4</sup> , fake or real news dataset <sup>5</sup> , and corpus	With limited datasets, pretrained algorithms like BERT and others do the greatest detecting fake news	On social media during the COVID-19 epidemic, could identify misleading and health-related fake news?

TABLE 2: Continued.

Authors (year)	Aim	Issues	Methods	Datasets	Findings	Shortcomings/future work
Shim <i>et al.</i> [50]	To avoid the distribution of fake news	Only propagation inside a single social media may be tracked when looking at the distributors' network.	link2vec	The fake news dataset in English and the dataset in Korean	A new source of background details for identifying false news that is successful in identifying short-form fake news	Further study is needed to determine how many top connections are ideal for maximizing the effectiveness of a fake news detecting system.
Samadi <i>et al.</i> [51]	To dive into comparison research regarding utilizing various classifiers and embedding frameworks	It is not clear which contextualized embedding will provide the classifier with the most useful characteristics.	CNN, single-layer perceptron (SLP), multilayer perceptron (MLP), BERT, RoBERTa, GPT2, and funnel transformer	LIAR, ISOT, and COVID-19	Achieve promising results without using additional features and network information increase the capacity of learning create dense contextualized embeddings for input texts	Has the ability to mine client profiles for additional information. Fake news may be detected using a variety of textual analyses in NLP.
Mhatre and Masurkar [52]	To determine the truthfulness of the news by scraping it from the internet	Increase the precision of categorization	Methods for NLP, like naive Bayes, KNN, decision tree, logistic regression, and the passive-aggressive classifier, or the SVM ensemble learning methodology	Web-scraped data	Fake news identification accuracy has increased; thus, the results may now be classified as trustworthy or untrustworthy	—

<sup>1</sup>“All data,” [Online]. Available: <http://drive.google.com/file/d/0B3e3qZpPtccsMFo5bk9lb3VCc2c/view>. <sup>2</sup>“Fake news samples,” [Online]. Available: <https://www.kaggle.com/pontes/fake-news-sample>. <sup>3</sup>“Fake news detection,” [Online]. Available: <https://www.kaggle.com/jruvika/fake-news-detection>. <sup>4</sup>[https://www.cs.ucsb.edu/~william/data/liar\\_dataset.zip](https://www.cs.ucsb.edu/~william/data/liar_dataset.zip). <sup>5</sup><https://www.kaggle.com/mrisdal/fake-news>.

TABLE 3: Performance of traditional machine learning and deep learning models.

Models	Datasets											
	Liar				Fake news dataset				Corpus			
	Acc	Prec	R	F1	Acc	Prec	R	F1	Acc	Prec	R	F1
SVM	56	56	56	48	67	67	67	67	71	78	71	72
Logistic regression	56	56	56	51	67	67	67	67	76	79	76	77
Decision tree	51	51	51	51	65	65	65	65	67	71	69	70
AdaBoost	56	56	56	54	72	72	72	72	73	74	73	74
Naive Bayes	60	59	60	59	86	86	86	86	93	93	93	93
k-NN	54	54	54	54	71	72	71	71	71	70	70	70
CNN	58	58	58	58	86	86	86	86	93	93	93	93
LSTM	54	29	54	38	76	78	76	76	93	94	93	93
Bi-LSTM	58	58	58	58	85	86	85	85	95	95	95	95
GAN	57	57	57	57	87	87	87	87	92	92	92	92

Note: Acc: Accuracy; Prec: Precision; R-Recall: F1-F1\_score.

of tagged data. SSLNews has a Politifact accuracy of 71.10 percent and a Gossipcop accuracy of 68.07 percent when utilizing data collected in the first 10 minutes after the news broke.

A deep learning algorithm is used in this article [42] to identify false news. Before the analysis, news articles are pre-processed utilizing a variety of training prototypes. A novel ensemble learning prototype for spotting false news has been developed, which combines four distinct models, including embedding LSTM, depth LSTM, LIWC CNN, and N-gram CNN to do so. To make false news identification even more accurate, the ensemble learning model's optimal weights are calculated using the Self-Adaptive Harmony Search (SAHS) method. Trials have shown that the suggested prototype outperforms existing approaches by 99.4%, as shown by the results of the tests we conducted. In addition, they look into the problem of cross-domain intractability and obtain a high degree of precision of 72.3%. When it comes to cross-domain intractability, they think the ensemble learning approach still has potential for improvement.

The study by Yanagi et al. [43] was done to better identify false information early on in its spread, and the researchers have developed a fake news detector that can create fictitious social contexts. Fake news generators are used to generate the fake context. Using a dataset of news items and the social environment in which they appeared, this model was trained to produce comments. As well as that, they developed a classification model. News stories, real-time remarks, and user-generated comments were all combined in this project. They evaluated the efficacy of their detector by comparing the performance of comments produced by the classifying model to comments generated by articles with actual comments. Because of this, they may say that examining a created comment is more effective at detecting false news than just analyzing genuine comments. As a result, it seems that our detector will be efficient in spotting false news posts on social media sites like Facebook and Twitter.

This article Paixão et al. [44] provided experimental analysis on the Fake.Br corpus, a fake news dataset in Brazilian Portuguese, utilizing supervised and unsupervised learning. They present a classification approach based on several kinds of characteristics and supervised deep learning algo-

gorithms for the identification of false news. In a comparison with other nondeep learning classifiers, their top classification model obtained F1 scores of up to 96 percent. Additionally, they conduct topic modeling on the same dataset using uni- and bigrams to offer a complimentary analysis.

Song et al. [45] presented a paradigm for multimodal false news detection depends upon crossmodal attention residual and multichannel convolutional neural networks (CARMN). Crossmodal Attention Residual Network (CARN) may selectively extract important information about a target modality from a source modality while keeping the unique information about the target modality. Convolutional neural networks can reduce the amount of noise introduced by cross-modal fusion components by concurrently obtaining textual feature representation from the originating text and the combined textual information. They carry out comprehensive tests on four real-world datasets and demonstrate how well the suggested prototype surpasses currently available methods and how it learns more discriminative feature descriptions.

Ren and Zhang [46] HIN, or hierarchical graph attention network (HGAT), is a novel architecture for the detection of fake news that makes use of a unique hierarchical attention method to carry out node description learning before identifying incorrect information. On two real-world fake news datasets, HGAT beats text-based frameworks or other network-based techniques. As a result of testing, their graph description learning or other node categorization-related apps in heterogeneous graphs may be expanded and generalized.

This work [47], a Multimodal Topic Memory Network (MTMN), that models intramodality and intermodality info in a single architecture, has been proposed that gathers and combines post descriptions held across latent topics using global features of latent topics. (1) In real-world scenarios, when newly incoming posts have various subjects spread from training data, their technique integrates a subject memory module to explicitly specify the end description as a post characteristic distributed among subjects and global features of latent topics. Robust representation is generated by first combining these two types of characteristics. (2) For multimodal fusion, they offer a new blended attention module that can concurrently achieve a high level of quality

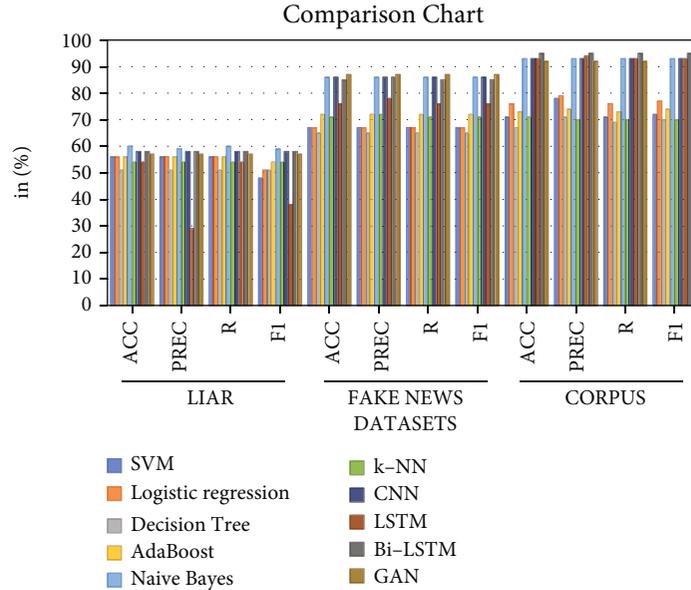


FIGURE 2: Bar graph comparison among three datasets for fake news detection.

description, make use of the inter- and intramodality connections within each mode, and also the link between the text words and the picture areas. Extended test on two public real-world datasets has demonstrated that MTMN exceeds other state-of-the-art methods.

Meel and Vishwakarma [48] have shown that fake news may be identified utilizing both text-based techniques like the hierarchical attention network (HAN) and visual picture features including such image captioning and forensic analysis working in concert. As an alternative to focusing only on one kind of multimodal data analysis, we used HAN text deep architecture, CHM, NVI, and Error Level Analysis (ELA) to create captions and headlines that matched the news content. A total of three datasets were used to evaluate each of these techniques separately but then collectively to use the max vote ensemble methodology. Observational data and comparisons using existing approaches show that the suggested strategy surpasses the current state-of-the-art on the fake news samples dataset with the greatest precision of 95.90 percent. Moreover, the findings show that the combined prototype outperforms individual approaches when it comes to correctly identify false information.

In this work, Khan et al. [49] performed benchmark research to evaluate the efficiency of various relevant ML techniques on three distinct datasets where they gathered the biggest and most diverse one. For the first time, they evaluated the effectiveness of several pretrained language prototypes for detecting false news with conventional and DL ones and looked at different elements of their results. Even with a limited dataset, pretrained algorithms like BERT and others do the greatest job of detecting false news. Because of this, these models are a much-improved choice for languages with little prototypes content, i.e., training data. In addition, they performed several analyses depending on the models' efficiency, the article's subject, and the article's length, and they highlighted various lessons gained from these.

In the research by Shim et al. [50], a new source of info for detecting false news has been proposed: the composition pattern of web links containing news material. This research offers a new embedding method called link2vec, an extension of word2vec, to correctly vectorize weblink composition patterns. For this study, they used two real-world fake news datasets in various languages to evaluate the efficacy of our link2vec-based model and its independence from language (English and Korean). The traditional text-based prototype and the hybrid model, which incorporated text and whitelist-based link information from a previous study, served as the comparative models for their research. Statistical significance was found in the link2vec-based detection prototypes, which beat all other comparison prototypes in both languages.

In the study by Samadi et al. [51], embedding input news items three classifiers with distinct pretrained models have been suggested. Following the embedding layer, which comprises new pretrained frameworks like BERT, RoBERTa, GPT2, and Funnel Transformer, we connect single-layer perceptron (SLP), MLP, and CNN to profit from deep contextualized description and deep neural categorization offered by these frameworks. LIAR, ISOT, and COVID-19 are the three well-known datasets for detecting false news. Based on the findings from these three datasets, their suggested algorithms for detecting false news outperform the current best practices. Classification accuracy improved by 7% on LIAR and by 0.1 percent on ISOT, respectively. A 1% improvement was also made on the COVID-19 dataset by their team of researchers.

In this work, S. Mhatre and Masurkar [52] devised a brand-new hybrid approach to spotting false news. Web-scraped data has been utilized to determine the veracity of two different news stories. The 1st method involves pre-processing the data using NLP methods such as text extraction, special-character removal, white-space removal, and stop-word removal. The next step is lemmatization, which organizes words based on their similarity in meaning. A

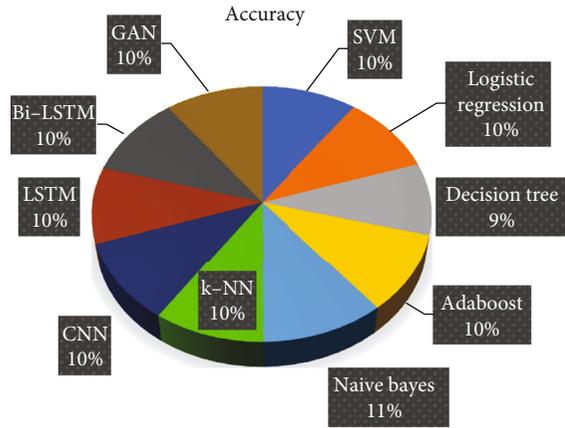


FIGURE 3: Pie chart for liar dataset.

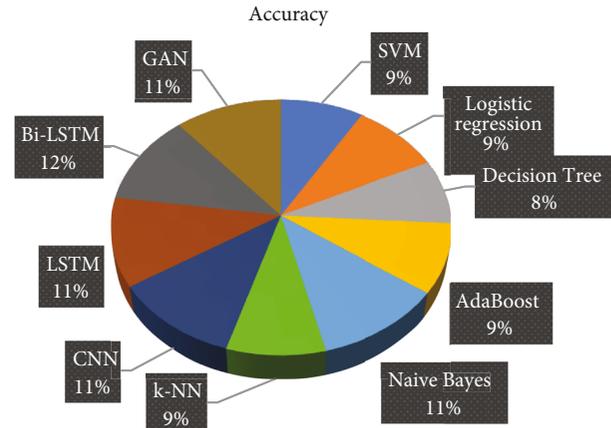


FIGURE 5: Pie chart for corpus dataset.

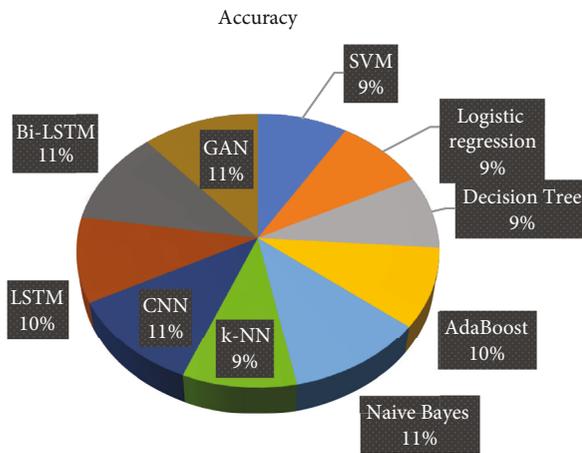


FIGURE 4: Pie chart for fake news dataset.

corpus is created after lemmatization using TF-IDF (term frequency-inverse document frequency) vectorization, and this is then utilized to train the models. To enhance classification accuracy, they suggest using a cosine similarity score that is derived from topic modeling and the corpus. There are a variety of classifiers used to evaluate whether or not the news is trustworthy, including logistic regression, passive-aggressive classifier, KNN Shrivastava et al. [22], decision tree, naive Bayes, and SVM. The passive-aggressive classifier, which is the most commonly used classifier in the identification of false news, has been given more attention to enhancing its classification accuracy. In the study of Zaamout *et al.* [24], the 2nd method employs an ensemble learning technique known as stacking, coupled with a cosine comparison score, to train a new prototype that determines whether the outcome is trustworthy or not. FND accuracy has been shown to improve with the second method (Table 2).

In Table 3, for the purpose of identifying false news, we compare the results of several conventional machine learning frameworks with a deep learning framework. On the corpus dataset, naive Bayes has the higher precision (93 percent) among conventional machine learning frameworks. For liar, the best framework is the default CNN framework, but we dis-

cover that it is only the second-best method overall. This dataset's output shows that LSTM-based frameworks are most susceptible to over fitting. Bi-LSTM suffers from over fitting as well on the liar dataset; yet, it is the third-best neural network-based framework depending on its efficiency on a dataset. There is a serious over fitting issue with text categorization methods like C-LSTM and HAN on a liar dataset. On the fake dataset, LSTM-based methods performed better, while CNN maintain their remarkable results. When used with corpus, LSTM-based frameworks operate best, with Bi-LSTM achieving a precision rate of 95% and an F1-score of 95%.

Figure 2 shows the comparison bar chart to three different datasets, liar, fake news, and corpus and evaluates the performance through different parameters. To our surprise, conventional machine learning frameworks fail miserably when it comes to spotting fake news, and instead, we discover that deep learning models exceed them. When applied to big datasets, such as corpus, the difference becomes more apparent, demonstrating that deep learning prototypes are more susceptible to over fitting. But despite being a conventional method, naive Bayes demonstrates tremendous potential in detecting false news, nearly reaching the efficiency of DL models and obtaining 93% precision on corpus, despite its age. Although additional research shows that naive Bayes' efficiency approaches saturate and increases extremely sluggishly with increasing sample size, the deep learning model's efficiency (i.e., Bi-LSTM) increases at a faster pace as the amount of training data increases. Deep learning methods may be able to surpass naive Bayes given enough training data; thus, this conclusion may be drawn.

Figures 3, 4, and 5 illustrated the pie chart to represent the accuracy ratio using different machine learning and deep learning algorithms. Figure 3 represents the pie chart for the liar dataset, while Figure 4 represents the pie chart for the fake news dataset, and Figure 5 represents the pie chart for the corpus dataset.

### 13. Conclusion

Even though the probability latent semantic analysis has a high rate of success in detecting false news and postings,

nevertheless, the constantly shifting qualities and features of false news on social media networks make it difficult to classify. DL, on the other hand, is characterized by the ability to calculate hierarchical characteristics. With the deployment of DL research and applications in the current past, many research works will apply DL techniques including CNNs, deep Boltzmann machines, DNN, and deep autoencoder models in different apps, including such audio and voice processing, NLP but rather modeling, info retrieval, objective recognition, and computer vision, and also implementing DNNs. In this comprehensive study, the basic concept of fake news detection has been described in detail with their types, features, and characteristics, and also the taxonomy for the fake news detection model has been described. Various fake detection methods have been implemented to identify user behavior by spreading rumors or fake news. The comparison has been made for numerous traditional machine learning and deep learning techniques on three liars, fake news, and corpus datasets. This comparison found that deep learning techniques outperformed traditional machine learning techniques. In this comparison, Bi-LSTM has achieved the best detection rate for fake news and obtained 95% accuracy and F1 score. This study will be helpful for further research in identifying fake news and the development of new models or tools for early detection. Another useful outcome is the fact that this research can be utilized by the cyber cell of police department and will be helpful in adopting appropriate means and method for dealing with fake data resulting in the betterment of the society. The only limitation that can be observed is that the analysis is performed on textual data, but in future, it can be elaborated for image data as well along with text to produce analysis results in a much wide and heterogeneous dataset.

## Data Availability

The data that support the findings of this study are available on request from the corresponding author.

## Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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