INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD)
© 2026 IJNRD | Volume 11, Issue 10, October 2026 | ISSN: 2456-4184 | IJNRD.ORG

IMPROVING FAKE NEWS DETECTION TECHNIQUE WITH BERT

[1]Varun, [2]Rahul Mishra

[1]Master's Student in Information Technology, C-DAC Noida, India
[2]Assistant Professor, C-DAC Noida, India

Abstract: This paper aims to explore alternative methods to detect fake news that is widely spread over social media, blog websites, news websites, etc. Nowadays fake news has become a major problem that is affecting global society. One of the hardest problems now is figuring out what news is true and what is phony in the actual world. Social networks, blog websites, and news websites are the common sources from which it is quite easy to access information anytime and anywhere throughout the globe. To address the problem of text-based fake news, a method is disclosed to detect the fake news by understanding the context of the text using the Bidirectional Encoder Representations from Transformers (BERT) Pre-Trained Natural Language Processing Model (NLP). In this method, the BERT model is used to receive the sentences as input and convert the text into vectors based on the context. The vectors identified using BERT are then submitted to the Naive Bayes and Logistic Regression machine learning model which processes the vectors classifies the sentences and provides the results in terms of accuracy. Further, this method also discloses a fake news detection user interface that utilizes the detection method, wherein the user can input the news title, author, and text. The backend system receives input from the user, processes it, and determines whether the input text is fake or real to the user at the user interface.

IndexTerms **- Fake news detection, fake article detection, NLP, BERT, user interface, detection interface.**

INTRODUCTION

Fake News is a piece of information that is copied from the news media but not into the organizational processes with the purpose of copying. Fake news does not contain any useful or factual information according to norms, it does not even contain any official information, it does not contain any verified content, and it does not follow any legal process of publishing news which does not ensure that this particular news is valid or not [1]. Fake news combines other incorrect information, such as misleading information, and inaccurate or deceptive information, and includes erroneous information that is spread among the public via social media and other connected platforms without the appropriate controls. Fake news includes not only political information but also other false material that lacks credible proof from a variety of websites and social media channels, which can lead to rumors and disturbances in society. Fake news is now spread a huge amount on different platforms. Fake News is a serious concern that negatively affects our society. Due to increasing of the user base of websites and apps that use larger platforms of social media, including Facebook, Twitter, Instagram, and WhatsApp where a variety of information, posts, news, and articles are shared daily, and sharing misleading or fake news as a result it causes false information, fraud news, and rumors in many cases. The fake news is written to deceive readers into thinking that it is true, so as a result it causes rumors and then riots [2].

There are many applications of automatic fake news detection using the BERT model as BERT has many advantages in that it understands the context of the text. So, as it understands the context of the text the input text is converted into the vectors based on the context and in a meaningful way. The automatic fake news detection system does not need much human interaction and does not need to manually analyze each article; this system can automatically identify real and fake news by just using the user interface which saves much time. The proposed approach used in this research archives above 98% accuracy as the text is converted into vectors using BERT that understand the meaning of the text. BERT performs NLP tasks including text categorization, machine translation, named entity recognition, and text representation. As in this research, BERT is used as the vector representation only so there is no need for another model for the text context analysis. As the BERT here is only used as a vector representation, the main advantage is that there is no need for any high-end systems for processing, the system does not need to be run in the background all the time so, it consumes low bandwidth and can easily work in any user devices without any hardware or software dependency.

When in this research BERT is used as the vector representation only so, to classify the input text for fake and real information, and evaluate the accuracy of the proposed model Naïve Bayes and Logistic Regression are used. The advantage of combining the "Naïve Bayes with the BERT model is that it can handle both continuous and discrete data and does not require a large quantity of training data", the obtained accuracy is based on the context identified by the BERT model and it can provide much higher accuracy when the continuous training of new data is performed. The advantage of using the logistic regression with BERT is that it can also apply to other kinds of machine learning methods, it can also work best when the dataset is separable linearly, and further provides valuable insights based on the text meaning related to the fake news identification data. Fake news identification can be automated by using machine learning and artificial intelligence models, such as BERT [9], various transformer-based methods, or embedding-based techniques, like Word2Vec. The models not only detect fake news but they can differentiate the real and fake information. Fake news detection can help society to be aware of true and false information help to avoid spreading false information and reduce the rumors that affect society. The automatic false information detection system offers us the ability to classify and automatically determine which news is true and which is fake, allowing us to halt the dissemination of news to a certain extent. Fake news identification can be automated by using machine learning and artificial intelligence models, such as

"BERT or other transformer-based models" [10], or embedding-based approaches, like Word2Vec [11]. The models not only detect fake news but can differentiate the real and fake information. Fake news detection can help society to be aware of the real and false information helps to avoid spreading false information and reduce the rumors that affect society.

This paper also focuses on developing a "user interface" (the features of the user interface are shown in the next sections) by utilizing the trained model using BERT and classification models. The user interface (UI) is responsive and simple to use so that a single user or a group of users can distinguish between articles and information shared on social media or blog websites. The front-end system is a web-based system that can be accessed by using a conventional web browser easily, anytime, and anywhere. The system can be easily implemented in the local area network server within the organization or the system can be implemented on the cloud network for public use such the front end users can access this system anywhere in the world. Based on earlier research and its findings, the false news recognition system faces several difficulties. "Several models based on AI approaches have been developed to detect false news on social media platforms" using a variety of effective strategies and features; however, "based on relevant studies and their conclusions", the results still need to be improved upon to boost accuracy. According to the research [12] the "challenges of fake news detection can be based on the dataset, overfitting/underfitting, features vectors, ML models used", etc.

In any machine learning or artificial intelligence research, the dataset selection and the analysis of the dataset are the biggest challenges as it is the most significant part of training the machine learning models, a wrong dataset selection may cause inaccurate results and inaccurate models [13]. As a result, accurate fake news dataset selection can able to provide accurate results. The challenge also concerns the size of the dataset, as during training the fake news dataset size generally varies. Smaller the size of datasets may give wrong results or the system does not work accurately in real-time and with a very large dataset the model may not support sometimes and cannot be analyzed [14]. Overfitting and underfitting pose significant challenges to models based on "artificial intelligence (AI) and machine learning (ML)" [15]. ML models that are Overfitted learn in a way that is unrelated to the training sets and lose their ability to be broadly applied to the whole population. One scenario that might result in overfitting is when there is not enough training data huge amounts of noise or unimportant information in the training set [16]. When a model can't correctly "represent the correlations between input and output variables, it's said to be underfitting. Because of the resulting skewed data, this increases the error rate in both the training and test sets" [17].

The choice of appropriate feature extraction techniques can also affect the accuracy of false news detection. For example, "sequence-based models need the processing of long text features". Several "fake news detection models have been developed in earlier studies"; however, the majority of these models rely on textual features, making them unsuitable for learning text-based representations [18]. Feature vectors are represented based on the context and meaning is suitable for real-life scenarios as fake news spreads a lot that does not include any meaning, the model can include BERT-based models that can understand the text and identify the vectors based on the meaning of the sentence [19]. The main challenge occurs in the selection of the right machine learning model that can handle the task of fake and real news detection when the text is vectorized using the BERT model. Another challenge arises concerning classification performance, large datasets are too difficult for typical machine learning to examine, which results in poor classification performance. This is because it is difficult to optimize "feature design, feature selection, and model training" [20]. Many researchers discuss ways to increase the accuracy of the fake news detection system, but they rarely discuss the final products used by the users. The task at hand is to develop a UI system that will enable end users to distinguish between fake and real-time information. The challenge of the system includes in terms of quality of the user interface, detection rate, user-friendliness, time to detect the information, etc. The challenges to developing end products are mostly tried to resolve in this research work.

In this research, we also proposed a unique prediction cycle after obtaining the final results. This cycle will continuously train the model as the model receives the inputs from the user via the user interface. Due to continuous training of the model, it provides higher accuracy. Further during the analysis, we ran a total of 10 cycles for both Naïve Bayes and Logistic Regression models that gave the accuracy more than 98%. One of the research's contributions is the BERT model, which uses the sentence's context to translate text into vectors. "In this study, two models—Naïve Bayes and Logistic Regression"—that yield the same accuracy on the Kaggle dataset are utilized. In actuality, Naïve Bayes performs better than Logistic Regression. "This study is divided into several sections: section 2 outlines the literature review that highlights earlier research efforts; Section 3 outlines the suggested methodology that highlights the actual research efforts; Section 4 outlines the findings and analysis; Section 5 outlines the proposed fake news detection system's user interface; and section 6 outlines the study's conclusion and future directions".

NEED OF THE STUDY.

Due to the increasing and spreading of fake news, there is a need for an efficient automatic fake news detection system that can automatically distinguish between fake and real news without the need for the human with higher accuracy. Numerous scholars have conducted extensive research on automatic systems for detecting fake news, employing a variety of methodologies and models to differentiate or recognize authentic news from fake news in input text. Taha et al. [3] use "COVID-19-based news and the BERT model to detect fake news". Zhang et al. [4] use "a BERT-based fake news detection model to detect fake information from the input data". The "Bidirectional Encoder Representations from Transformers (BERT) model" is a pre-trained bidirectional model that understands the meaning of sentence bidirectional (i.e. understanding the sentence left-to-right as well as right-to-left simultaneously). It undergoes pre-training on two natural language processing (NLP) tasks: "next sentence prediction (NSP) and masked language modeling (MLM)" [5]. The MLM hides the word in a word and predicts the hidden word and the NSP predicts the logical, sequential connection for the two sentences. BERT consists of two steps: fine-tuning and pre-training. During pre-training, the model is trained on unlabeled data from several pre-training tasks [6, 7]. The BERT model is initialized for fine-tuning using the pre-trained parameters [8], and each parameter is adjusted using labeled data from the downstream jobs.

LITERATURE REVIEW

2.1 Transformer Based Models

Kaliyar, et al. [2] "integrates the BERT with different parallel blocks of the single-layer deep Convolutional Neural Network (CNN), it propose a deep learning technique called FakeBERT that is BERT-based (Bidirectional Encoder Representations from Transformers)". Azer, et al. [3] describe to detection of fake information by training only a COVID-19-based news dataset. "Five machine learning techniques and deep learning models were evaluated. The proposed approach blends bidirectional encoder representations from transformers (BERT) with deep learning models". Zhang, et al. [4] create a multi-labeling, multi-class algorithm for testing false news. It uses a dataset from the MediaEval 2022 fake news detection competition, which included texts from Twitter. To complete the text classification task in the MediaEval 2022 fake news detection challenge, the author suggested "a Bert-based multi-label multi-category fake news detection model". Aljawarneh, et al. [21] "satisfied the requirements of the fake news identification assignment and developed an improved BERT model. The last layer of this model was unfrozen and trained on news texts to yield the most precise representation of the incoming content". The Kaggle website was used to obtain the information. The BERT model was only used as the classification algorithm to obtain results. Pal, et al. [22] "developed a small model that aids in the detection of fake news. The dataset gathered from the internet has either real or fake labels. Various machine learning methods, including Passive Aggressive Classifier, Logistic Regression, Naïve Bayes, Long Short-Term Memory (LSTM), Decision Tree, and Bidirectional Encoder Representations from Transformers (BERT), were used". Farokhian, et al. [23] "present MWPBert, which performs veracity detection on full-text news articles using two parallel BERT networks. One BERT network encodes the news body, while another encodes the news headline. The outputs of the two BERT networks are encoded into an output network".

2.2 Traditional Approaches

Elhadad, et al. [24] describe "a method for spotting false information that draws on data from the UN, WHO, UNICEF, and fact-checking websites as well as offensive material". Datasets with fact-checking were gathered related to COVID-19 information. The "TF-IDF and Word Embedding algorithms were employed to extract features from the dataset. The model is trained with Naïve Bayes, Decision Trees, Linear Regression, KNN, Perceptrons, and Neural Networks". The authors [25] "proposed a model for fake news detection by collecting the dataset from multiple sources and merging them into a single large dataset". The dataset is trained to predict the sentiment using social media data that is positive or negative. The TF- IDF is utilized for feature extraction techniques and sentiment scores and uses Naïve Bayes and Random Forests to predict accuracy. Kaliyar et al. 2019 [26] "proposed a technique to enhance the identification of news that circulates in our culture, both legitimate and bogus using ensemble machine learning based on trees (Gradient Boosting) with optimum settings" [27]. The multiclass dataset is obtained from the Kaggle. It then converts the text into vectors using the TF-IDF method. Chauhan, et al. [28] "proposed a solution for detecting fake news. This study extracted the unique elements to determine whether the news is false or accurate, as well as the confusion 4x4 matrix, which means using four labels instead of two". It obtains the Facebook dataset from the Buzz News Feed, trained using the K-Nearest Neighbor classifier. Julio C. S. Reis, et al. 2019 [29] concentrated on identifying and understanding social media-disseminated fake news items. The features are Lexical features, Language features, semantic features, and psycholinguistic features. "The features were converted into vectors using the TF- IDF technique. The data is trained using four machine-learning algorithms".

Jain & Kasbe. [30] Developed a technique to identify fake news and used the Web scraping approach to do it on Facebook. A dataset was obtained from GitHub and used the Naïve Bayes for the training dataset. The vocabulary is generated using bag-of-words, the features were extracted and converted text into vectors in the form of a sparse matrix, and then the Naïve Bayes classifier. Granik & Mesyura [31] use the Naïve Bayes Classifier to identify bogus news on Facebook. The Facebook articles are collected from the BuzzFeed news site. Then the data is preprocessed and extracted features from the dataset using a count vectorizer. Abedalla, et al. [32] describe "the strategy for detecting bogus news using deep learning techniques. Using the Fake News Challenge (FNC-1) dataset, it develops algorithms to detect bogus news based on the relationship between the article's headline and body. It uses Convolutional neural networks (CNN), long short-term memory networks (LSTM), and bidirectional LSTM (Bi- LSTM) models". Helmstetter & Paulheim [32] describe "an alternative approach to generate a large dataset for tweet classification with minimal human involvement". The method uses loose supervision and automatically compiles millions of tweets into a large, noisy training dataset. The tweets are categorized into trustworthy and untrustworthy sources as a weak monitoring signal and use this dataset to train a classifier.

Ramya, et al. [33] compare and assess various machine learning methods used in various social media sites. These methods include "deep learning algorithms like CNN, RNN, and LSTM, and categorization algorithms like Naïve Bayes". The models trained using just one deep learning technique; models trained using a hybrid of two deep learning techniques—such as merging two CNNs or combining CNN and LSTM-RNN. Alameri & Mohd [34] "compare the effectiveness of two Machine Learning models, Support Vector Machine (SVM) (NN-TF) and Naïve Bayes (NB), as well as three Deep Learning models: Long Short-Term Memory (LSTM), Neural Network with Keras (NN-Keras), and Neural Network with TensorFlow". Mathews & Preethi [35] addresses the issue by automatically identifying "false news based on its substance. The support vector classifier (SVC) is used to assess the approach's performance on the ISOT dataset". Ahuja & Kumar [36] developed "an S-HAN model to identify fake news. To help with the identification of misleading information, the model uses stacked bidirectional Gated Recurrent Units (GRU)", which are an enhanced version of Hierarchical Attention Networks, to recognize the important words and phrases in the news. Barua, et al. [37] "address the problem of fake news by determining whether a news article is accurate or deceptive". Modern recurrent neural network ensemble techniques were used to accomplish LSTM and GRU. The validity of a news story was ascertained using an Android app.

Kaur, et al. [38] describe a brand-new ensemble model for multi-level voting is put forth. "Which classification model correctly detects false features (HV) is determined by applying feature extraction approaches such as Count-Vectorizer (CV), Hashing-Vectorizer, and Term Frequency-Inverse Document Frequency (TF-IDF)". Patwa, et al. [39] "proposed a model for detecting fake news to address the issue of fake news. A hand-annotated dataset of news articles and social media messages on COVID-19 has been trained using Decision Tree, Logistic Regression, Gradient Boost, and Support Vector Machine". Bharadwaj, et al. [40] "present a strategy for identifying fake news in online articles using a variety of machine-learning methods and semantic features. It is a comparative study of recurrent neural networks and random forest and Naïve Bayes classifiers using five sets of language features from the Kaggle dataset". Poddar, et al. [41] use a geometric and probabilistic machine learning computational approach to tackle the false news issue. "It examines the output of two distinct vectorizers, count and Term Frequency Inverse Document Format (TF-IDF), to determine which best vectorizer for identifying fake news is. The model was trained using decision tree classifiers, Naïve Bayes, Support Vector Machines (SVM), and Logistic Regression". Bali, et al. [42] "proposed a method for detecting false news that makes use of natural language processing and machine learning techniques. Three conventional datasets were evaluated using a novel set of features that were taken from the headlines and contents". Al Asaad, et al. [43] proposed that "techniques for machine learning and supervised learning are used to identify false news. Using a dataset of real and fake news, the model was trained using a machine learning model in Python using the Scikit-learn module. Applying text analysis techniques such as Bag-of- Words, Bi-gram frequency, and Term Frequency-Inverse Document Frequency (TF-IDF)". Kalra, et al. [44] use the Fakeddit dataset—a compilation of in-depth articles and relevant photos—to look at the task of spotting false information. "It proposes a multimodal approach based on transfer learning to gather contextual and semantic data, reinforce latent representations between words in news samples and images, and try to improve the accuracy of the FND task".

Alzubi, et al. [45] suggest an EdgeFNF strategy for a mobile architecture that is fully Edge- to-Cloud. After gathering data from social media platforms, "EdgeFNF preprocesses it on a mobile edge node and sends the metadata to a cloud server for text data processing using several techniques, such as Natural Language Processing (NLP) [46]. To ascertain if the news is true or false, data is constantly transferred from the social media application to the cloud server". Tida, et al. [47] introduced the challenge of false news identification is addressed by "the unified training method, which uses a pre-trained transformer model as the foundation structure for the classifier and all hyperparameters from individual models. Three publicly available datasets, including ISOT and Kaggle, were utilized. Long Short-Term Memory (LSTM), Random Forests, and Convolutional Neural Networks (CNN) are all included in the model". Cui, et al. [48] propose "a technique for detecting false news that makes use of a Third-order Text Graph sensor in an Intra-graph and Inter-graph Joint Information Propagation Network (IIJIPN)". "To establish homogenous information interaction within each graph, intra-graph information propagation was carried out, and by stacking the propagation layer, high-order homogeneous information interaction was accomplished within each graph". Yang, et al. [49] "propose a Dual Co-Attention Network (Dual-CAN) that uses news content, social media comments, and everlasting knowledge as inputs to detect bogus news". The proposed Dual- CAN performs better in two benchmark datasets than the current representative models.

2.3 Embedding based models

Anjali, et al. [50] "propose a method for employing machine learning to identify fake news. Nave Bayes, Neural Network, Long and Short Term Memory (LSTM), and Support Vector Machine (SVM) are the four machine learning models it uses. The Doc2Vec model is used to transform the text into vectors after the data is gathered from the Kaggle website". Singh [51] "presents a model to detect fake news in some vector space, utilizing a combination of standard mathematical operations". The LIAR and the Kaggle Dataset [52] were obtained. "The dataset was preprocessed and encoded using one-hot encoding, TFIDF, Word2Vec, and Doc2Vec. It then applies models of Artificial Neural Networks (ANN), convolutional neural networks (CNN), and recurrent neural networks (RNN)". Huang & Chen [53] developed a paradigm for collective learning to identify false news. "It makes use of learning models including N-gram CNN, LIWC CNN, depth LSTM, and LSTM. The dataset was acquired via the Kaggle and GitHub platforms [52]. Word2Vec, n-gram models such as N-gram CNN, TF-IDF, LSTM, depth LSTM, and LIWC CNN are examples of word embedding systems". Shim, et al. [54] "propose an innovative embedding method called link2vec, an expansion of word2vec. The studies used two false news datasets: one in English and one in Korean. It vectorizes text using a link2vec vectorizer and employs three classifiers for training, validation, and testing Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Logistic Regression (LOGIT) on the English dataset".

Lyu & Lo [55] propose "a model to solve the problem of fake news using decision trees. The decision trees, doc2vec, the Support Vector Machine (SVM), and FakeNewsTracker are some of the tools used to evaluate the performance of various machine-learning algorithms. It uses the Twitter dataset for training the model and uses TF-IDF, and Doc2Vec models for converting text into vectors". Gravanis, et al. [56] "suggest a model for identifying fake news". It uses various feature sets for deception detection and word embedding to arrive at the most accurate model. It uses ensemble ML techniques like AdaBoost and Bagging with the "UNBiased" (UNB) dataset on word embedding, ensemble algorithms, and Support Vector Machines (SVMs). The author [57] suggests a novel method that builds numerous models that precisely classify news stories as authentic or fake using document embedding. Using precision, the models were assessed on five sizable news datasets. The complexity of the classification model was not the most crucial element for achieving high accuracy, according to the author, but rather the document encoding. "According to the above prior approaches, many researchers provide close solutions to differentiate between real news and fake news articles". However, many prior approaches are outdated; the prior approaches only describe the solutions in terms of improving the accuracy and their respective scores. The prior approaches do not describe text encodings that convert text into vectors based on their meaning bi- directionally, "due to which the model is not able to predict text accurately and affects the overall performance". Many prior researchers were even not able to achieve above 90% accuracy. It does not disclose the real-world scenario problem for detecting fake news.

The research [45] discloses "a solution to detect fake news in the real world using mobile devices". However, it does not provide solutions in terms of accuracy and scores, it further includes limitations such as the mobile devices must be connected to the network to detect fake news articles that consume more bandwidth of the user's mobile device. Moreover, there are no inputs taken from the user due to which the users do not have their own choice to identify fake news. So, this current research resolves the problems and limitations disclosed in the prior art to detect fake news and real news using BERT in terms of accuracy and their respective scores and discloses a system that "uses BERT and can able to differentiate the fake news articles and real news articles by taking input from the user". The advantage of this proposed research work is that user has their own choice to detect fake and real news from multiple sources, consume less bandwidth, and have fewer device limitations, which means a user- friendly system where a user can use any user equipment (such as smartphone, laptop, desktop, tablet, etc.) to detect fake news and real news articles. Our approach is novel to other authors. In our research work, "BERT is only used for word embedding, and different machine learning algorithm is used to determine accuracy, our model also works better as compared to approaches disclosed by other authors". So our model also works best and it depends on the training and testing of the model. We aim to improve the problem of word embedding for detecting fake news so BERT is only used as a word embedding model. When our model is trained during production it achieves 99% accuracy (See Section 4.4). The features of the user interface are shown in the further part. Additionally, the prior art did not disclose how to construct a user interface using a trained model, which will be beneficial in the future to discern between fake and true information in a real environment.

PROPOSED APPROACH

According to problems discussed in the above prior art, this paper proposed an approach to identify the fake and real news accurately. The model for false news identification presented in this proposed approach is explained in this section and is used to detect spurious (fake) news. In fake news detection especially for text data, one of the crucial and time-consuming jobs in "this proposed strategy is the employment of the natural language processing technique to identify fake news". There are given steps for this proposed research work and discussed further in detail with working examples. In addition, some steps explain how the work completed in this research works with outcomes for clear and better understanding. The steps of the suggested model that separates the text's genuine news from its fake news are shown in Figure 1.

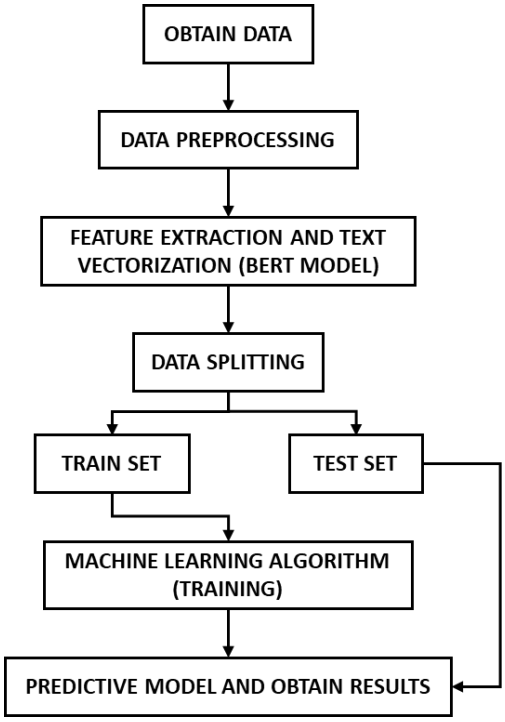
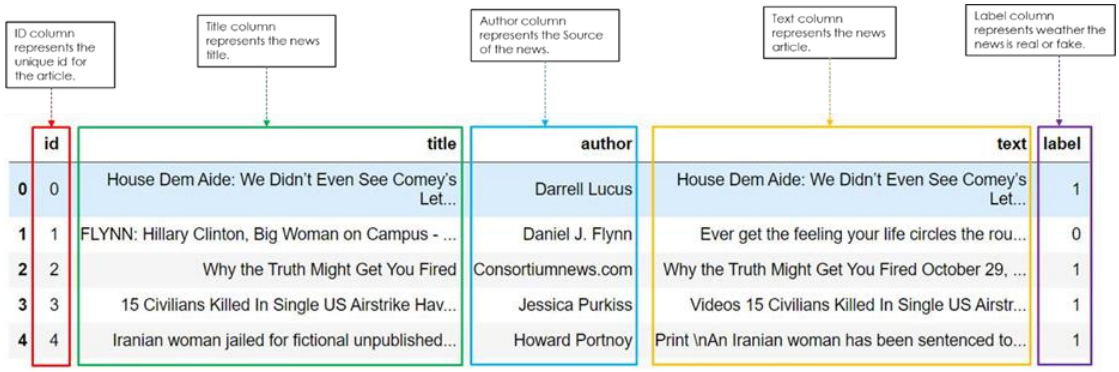


Figure 1: Proposed Approach

3.1 Obtain Data

Obtaining the labeled dataset is the primary goal of the suggested method or any machine learning model. "This step is very necessary to generate a machine learning model, based on the dataset the model will be trained". False datasets may cause wrong results and affect the overall accuracy. The data related to the news and information articles is collected from Kaggle which includes 2017 US elections news data obtained from "the news articles and social media articles collected from different sources such as news websites, blogs, social media such as Facebook, Twitter, etc.", and other websites. The obtained dataset comprises approximately a total of 26,700 news articles [52]. It includes columns such as ID that identifies the news article, Title that contains the headlines for the news, Author that contains the sources of news, Text that contains the news article, and Label that contains 1 and 0 labeled to each row where 1 denotes authentic news and 0 denotes fake news. Figure 2 describes the detailed overview of the obtained dataset.



	id	title	author	text	label
0	0	House Dem Aide: We Didn't Even See Comey's Let...	Darrell Lucus	House Dem Aide: We Didn't Even See Comey's Let...	1
1	1	FLYNN: Hillary Clinton, Big Woman on Campus - ...	Daniel J. Flynn	Ever get the feeling your life circles the rou...	0
2	2	Why the Truth Might Get You Fired	Consortiumnews.com	Why the Truth Might Get You Fired October 29, ...	1
3	3	15 Civilians Killed In Single US Airstrike Hav...	Jessica Purkiss	Videos 15 Civilians Killed In Single US Airstr...	1
4	4	Iranian woman jailed for fictional unpublished...	Howard Portnoy	Print \nAn Iranian woman has been sentenced to...	1

Figure 2: Dataset Overview

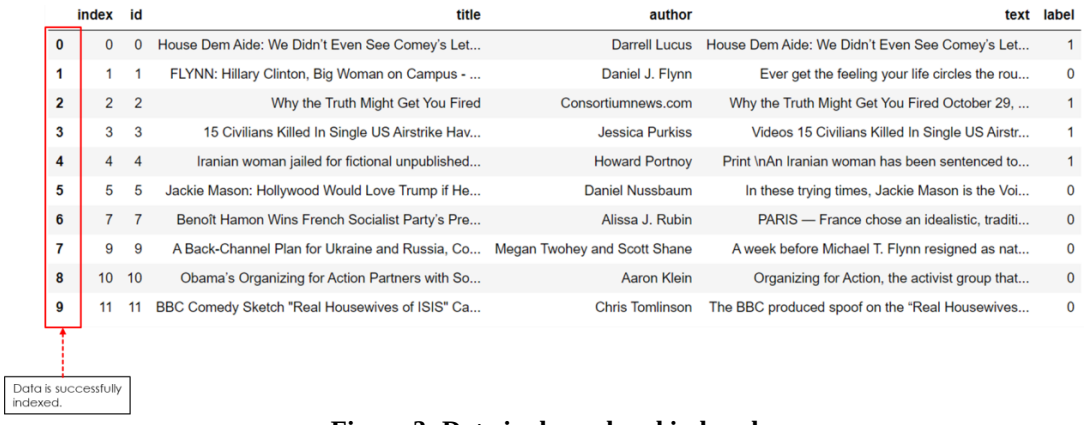
3.2 Data Preprocessing

After obtaining the dataset, the next task is to preprocess the data or clean data like removing duplicate rows, indexing of rows feature selection task, removing stop words, stemming and lemmatization, or any errors in the dataset, etc. This step is very necessary after obtaining the dataset, as we know that the raw set includes many unnecessary data and values that are not needed during analysis, the unnecessary data affects the overall performance and load on the system hardware. Additionally, this will also make analysis and decisions easier and increase overall accuracy. This will comprise combining the features title, author, and text into one attribute, this will give the one feature that is total and label which is the independent variable and this makes it easier to extract the word and analysis as discussed in further steps.

3.2.1 Data Cleaning

Data cleaning is the very first step of data preprocessing. The data cleaning includes removing null values that are empty rows in the dataset. The reason for removing null values is that the null rows create big problems in data analysis and other machine learning-related tasks. The problem may include the calculations, machine learning algorithm, and data visualization that cause the problem in the overall accuracy. So, in this step from the obtained data, the null rows are removed, and the new data includes the 26000 rows.

As soon as the null rows are removed there is a need to perform the re-indexing of the data that will uniquely identifies the row that is the article in the data. Wrong indexing in data may cause problems in the data visualization and cause errors in the analysis. For example, suppose there are 10 rows in the dataset having the row ID in the series of row 1, row 2, row 3, row 5, row 6, and so on. Therefore, we can see that the row ID is wrong after row 3 and it should contain row 4, and the indexing will solve this problem in the data. Figure 3 describes the null rows that are removed and the data is indexed correctly.



	index	id	title	author	text	label
0	0	0	House Dem Aide: We Didn't Even See Comey's Let...	Darrell Lucus	House Dem Aide: We Didn't Even See Comey's Let...	1
1	1	1	FLYNN: Hillary Clinton, Big Woman on Campus - ...	Daniel J. Flynn	Ever get the feeling your life circles the rou...	0
2	2	2	Why the Truth Might Get You Fired	Consortiumnews.com	Why the Truth Might Get You Fired October 29, ...	1
3	3	3	15 Civilians Killed In Single US Airstrike Hav...	Jessica Purkiss	Videos 15 Civilians Killed In Single US Airstr...	1
4	4	4	Iranian woman jailed for fictional unpublished...	Howard Portnoy	Print \nAn Iranian woman has been sentenced to...	1
5	5	5	Jackie Mason: Hollywood Would Love Trump if He...	Daniel Nussbaum	In these trying times, Jackie Mason is the Voi...	0
6	7	7	Benoît Hamon Wins French Socialist Party's Pre...	Alissa J. Rubin	PARIS — France chose an idealistic, traditi...	0
7	9	9	A Back-Channel Plan for Ukraine and Russia, Co...	Megan Twohey and Scott Shane	A week before Michael T. Flynn resigned as nat...	0
8	10	10	Obama's Organizing for Action Partners with So...	Aaron Klein	Organizing for Action, the activist group that...	0
9	11	11	BBC Comedy Sketch "Real Housewives of ISIS" Ca...	Chris Tomlinson	The BBC produced spoof on the "Real Housewives...	0

Figure 3: Data is cleaned and indexed

3.2.2 Combining data and removing stop words

In preprocessing the novel approach of this research is to first combine the words and then remove the stop words in the sentences. As discussed above the dataset includes the main columns title, author, and text. To make an analysis of text easier and more efficient, these three columns of text are combined into one total column. The advantage of doing this is to avoid loading to preprocess text separately on each three columns. Figure 4 describes the text of the three columns combined in one column named total.



	id	total	label
0	0	House Dem Aide: We Didn't Even See Comey's Let...	1
1	1	FLYNN: Hillary Clinton, Big Woman on Campus - ...	0
2	2	Why the Truth Might Get You Fired Consortiumne...	1
3	3	15 Civilians Killed In Single US Airstrike Hav...	1
4	4	Iranian woman jailed for fictional unpublished...	1

Figure 4: Combined title, author, and text features/columns

The next step is to eliminate the stop words after merging the three columns labeled title, author, and text into a single combined column called total. In text preprocessing the stop word removal is very important. The stop words should be eliminated from the text because they don't provide any important information. The stops are used frequently and hence their frequency is very high. This will help to analyze smaller data. The stop words can be removed by using any library such as Python NLTK or it can also be removed by manually entering the list of stop words. To make it easier and efficient in the case of real-time scenarios any stop word library can be used that includes a list of all the stop words. Figure 5 includes the list of stop words and is case-sensitive. This list is compared with our dataset and eliminates if the stop words are present in the dataset.

```
['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're",
"you've", "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he',
'him', 'his', 'himself', 'she', "she's", 'her', 'hers', 'herself', 'it', "i
t's", 'its', 'itself', 'they', 'them', 'their', 'theirs', 'themselves', 'what',
'which', 'who', 'whom', 'this', 'that', "that'll", 'these', 'those', 'am', 'i
s', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'havin
g', 'do', 'does', 'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or',
'because', 'as', 'until', 'while', 'of', 'at', 'by', 'for', 'with', 'about', 'a
gainst', 'between', 'into', 'through', 'during', 'before', 'after', 'above', 'b
elow', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under',
'again', 'further', 'then', 'once', 'here', 'there', 'when', 'where', 'why', 'h
ow', 'all', 'any', 'both', 'each', 'few', 'more', 'most', 'other', 'some', 'suc
h', 'no', 'nor', 'not', 'only', 'own', 'same', 'so', 'than', 'too', 'very',
's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now',
'd', 'll', 'm', 'o', 're', 've', 'y', 'ain', 'aren', "aren't", 'couldn', "could
n't", 'didn', "didn't", 'doesn', "doesn't", 'hadn', "hadn't", 'hasn', "hasn't",
'haven', "haven't", 'isn', "isn't", 'ma', 'mightn', "mightn't", 'mustn', "must
n't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn', "wa
sn't", 'weren', "weren't", 'won', "won't", 'wouldn', "wouldn't"]
```

Figure 5: List of Stop Words that are removed from the dataset

While preprocessing the stop words are removed very carefully without affecting the meaning of the sentence. For Example according to the stop words list it includes ‘us’ and there is a sentence that is ‘I live in the US’ so the stop word will be removed as its case is the same and present in the list, I will not be removed as it has a different case (i.e. UPPERCASE) removing I will change the meaning of the sentence, similarly the US will also not removed as it denoted as the country and also the case is not present in the list. So, the sentence still defines the rough meaning after removing stop words and this is the main goal of this preprocessing step. The stop words that were eliminated from the 26000-row dataset are shown in Figure 6.



	total	label
0	house dem aide we didnt even see comeys lette...	1
1	flynn hillary clinton big woman campus breitb...	0
2	why truth might get you fired consortiumnewsc...	1
3	15 civilians killed in single us airstrike ha...	1
4	iranian woman jailed fictional unpublished st...	1

Figure 6: Stop words removed

3.3 Features extraction and text vectorization (Applying the BERT Model)

After data preprocessing the main task is to accurately perform feature selection, and text vectorization (converting text documents in the form of some token IDs (See Fig. 7) and the form of vectors), this stage involves the use of a natural language processing technique with a pre-trained BERT model. The primary objective of this research work is to obtain word vectors by understanding the meaning of the sentence in multiple dimensions (such as in 780 dimensions or it can also be above 780 dimensions). The reason for using the BERT is that the BERT technique is a semantics-based technique, which means that this natural language technique will be useful for the real-based scenario.

Using the encoder portion, BERT aims to generate the language representation model. The sequence of tokens—known as the [CLS] or "101" tokens—is fed into the encoder portion. At the start of the paragraph, a unique token called [CLS] or "101" is added, This token is used for the classification task and makes the machine that the news sentence has started. The [SEP] or ‘102’ is also a special token that is added at the end of the sentence to denote the end of the sentence for the machine. This is necessary because a machine-learning model cannot understand the text and the text should be converted into some form of ID to denote the unique numbers. Figure 7 describes converting the text sequence into tokens.

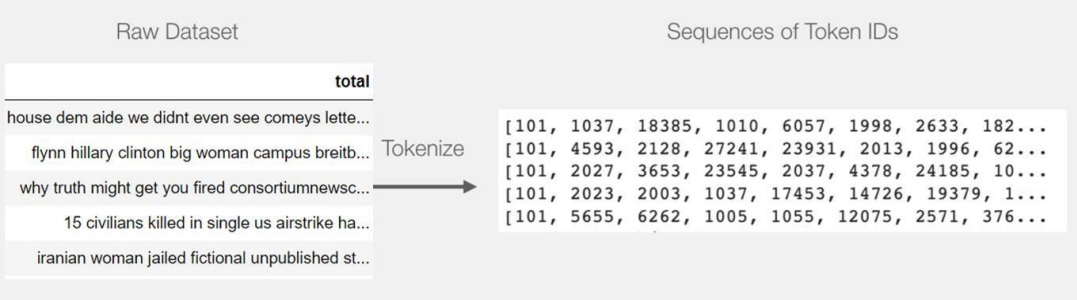


Figure 7: Converting text into IDs based on the text sequence

After converting the text into a sequence of token IDs. The text assigned with the token IDs is then converted into vectors. The vectors denote the high-quality feature inputs for the classification models such as "Naïve Bayes and Logistic regression". The BERT converts each word into 768 dimensions. The dimensions provide information about word combinations, which aids in deciphering the meaning of the term used in the sentence. For example, the word 'bank' has two meanings, first the bank of the river and the financial bank. If the word bank is used with the sentence that describes the bank of a river the model creates different vectors in 768 dimensions. If the word bank is used with the financial bank, the model generates different vectors in 768 dimensions. Therefore, the text converted into multiple dimensions gives the advantage as compared to one hot encoding used in the prior research. Whereas the Word2Vec does not work intelligently like BERT. Figure 8 describes how the text is converted into vectors having multiple dimensions based on the identified tokens.

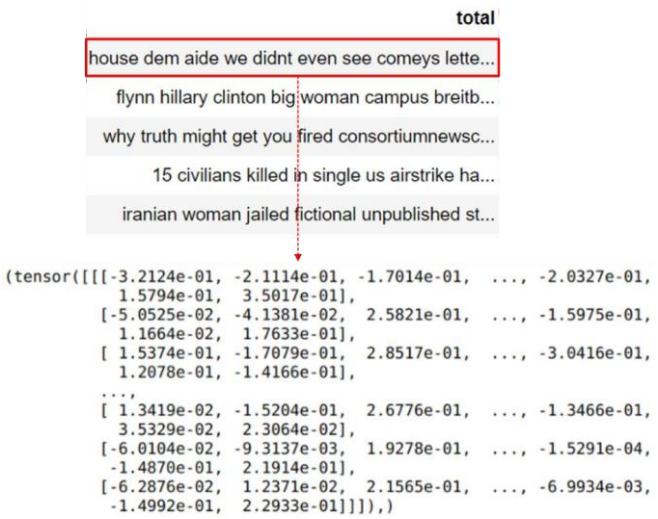


Figure 8: Text converted into vectors and each text has multiple dimensions

This step is the main novel step of the proposed work. To understand there is a need to first understand how the BERT model works as described in the next section. In this proposed approach, "BERT is only used to convert text into vectors". Any text-processing task in any real-world scenario meaning identification is very important, especially in identifying fake news where the prior approaches lack identification of the meaning of the text in the fake news identification. Therefore, the BERT plays a very big role in this research work.

3.4 Data Splitting

A crucial stage in every machine-learning investigation is data separation. "The dataset is divided into a training set and a test set" for analysis and performance, which is a crucial component of any machine learning analysis, as shown in Figure 9. After the text, preprocessing a total of 26000 rows were obtained. The 20800 rows are chosen for the training set and 5200 rows are chosen for the test set out of a total of 26000 rows. This indicates that in this study, "the training set has 80% of the data, while the test set contains 20%". The test set is used to forecast performance and to get the results, while "the training set is utilized to train the machine learning model". The train set and test set are distinct from one another and contain separate text data.

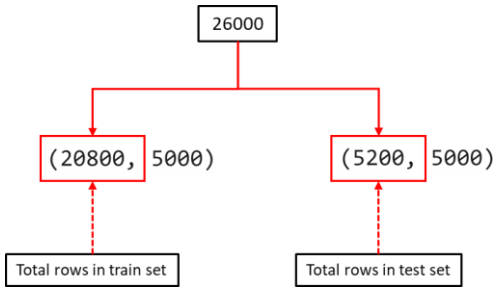


Figure 9: Dataset Splitting

3.5 Applying the Machine Learning Model

To distinguish between bogus and true news, the "Naïve Bayes and Logistic Regression" models are applied independently in this step. The two models utilized for result classification are machine learning models following the division of the data into the test and train sets. "Naïve Bayes and linear regression are used to train the machine-learning model on the train set". The resulting vectors are fed as input into the classification model for training. On the test set, the accuracy of the predictions, performance, and outcomes are measured. Obtained results compared to the previous research work performed by different authors, and an analysis is performed and identify the reason for the previous research work, to identify the problems in the prior work and advantages of the current work.

The model has trained again in cycles unless constant accuracy is achieved. This research works much better after using the BERT Pre-Trained model for text vectorization. As a result, the confusion matrix is also generated using 0 (fake) labels and 1 (real) label which helps to decide how many predicted values are real when actual values are real and how many predicted values are fake when actual values are fake. This analyzes and predicts the results such as error rate, AUC, and F1-Score accuracy obtained. Figure 10 describes that the obtained vectors are sent as an input to the "Naïve Bayes and Logistic Regression" Model to compare the performance of both models.

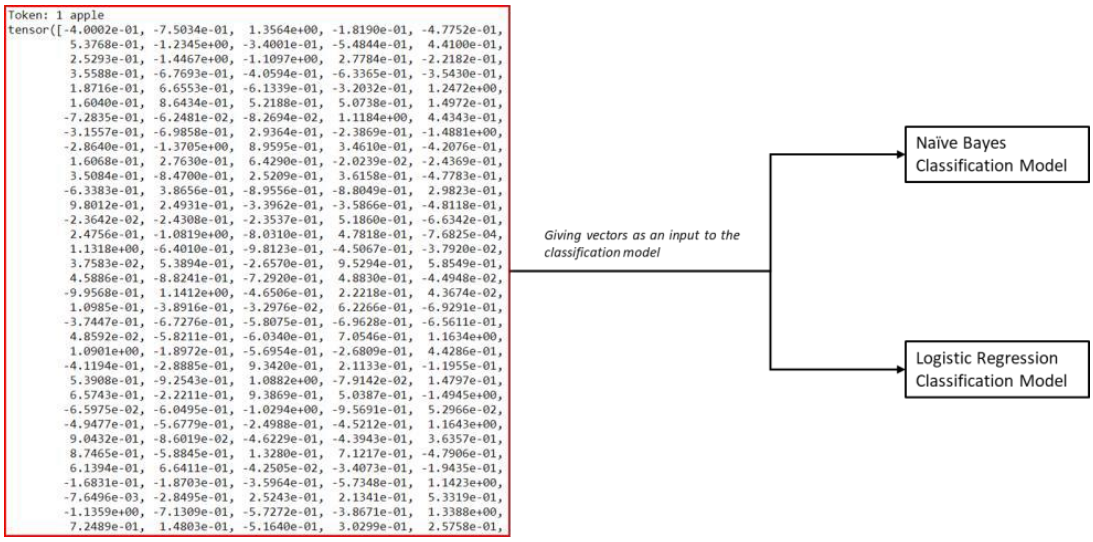


Figure 10: Vectors as an input to the classification model

4. Results and Analysis

4.1 Performance Metrics

The confusion matrix is used to assess the model's performance. "The confusion matrix is a highly helpful tool for measuring F1-Score, Recall, Accuracy, Precision, and the crucial AUC- ROC Curve". The following are included in the confusion matrix: "False Positive indicates that actual news is false but predicted news is real; False Negative indicates that actual news is real but predicted news is fake; and True Negative indicates that both actual and predicted news is fake". Given the correctness of the results obtained. "The percentage of accurate predictions to all predictions made is known as accuracy". It indicates the percentage of anticipated values that are accurate. Equation 1 provides the accuracy formula.

$$\text{Accuracy: } \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

In machine learning, the first thing we do with data once it has been cleaned, preprocessed, and organized is feed it to a top-notch model, from which we naturally obtain the output in probabilities. In this instance, we employ a confusion matrix to assess these kinds of difficulties since the more effective the solution, the higher the desired performance. The performance metric for a machine learning classification task, which may involve two or more classes, is the confusion matrix. There are four possible combinations of expected and actual values in this particular sort of 2x2 matrix. An illustration of a confusion matrix is provided below. The confusion matrix for the Naïve Bayes algorithm is shown in Fig. 11(a), while the confusion matrix for the logistic regression is shown in Fig. 11(b).

Considering Fig. 11 (a) the confusion matric for Naïve Bayes the predicted real (1) values and actual real (1) values are 2493, the predicted fake (0) values and actual fake (0) values are 2592, the predicted real (1) values and actual fake (0) values are 71, and the predicted fake (0) values and actual real (1) values are 44. Now considering Fig. 11 (b) the confusion matric for Logistic Regression the predicted real (1) values and actual real (1) values are 2558, the predicted fake (0) values and actual fake (0) values are 1783, the predicted real (1) values and actual fake (0) values are 6, and the predicted fake (0) values and actual real (1) values are 853.

Now observing the values given in Fig. 11(a) for Naïve Bayes and Fig. 11 (b) for Logistics Regression the Naïve Bayes works much better than the Logistic Regression even the both have the same accuracy. The reason that the Naïve Bayes works better than the predicted real and fake is, that actual real and fake values are much higher than analyzed by the logistic regression and that is only needed for the real-world scenario. Observing Fig. 11 (b) for Logistic Regression the predicted fake (0) and actual

real (1) values are 853 much higher than the Naïve Bayes and that is not expected for real-world problems it means that 853 values are predicted as fake (0) wrongly as the actual values are real (1). So, as a result, there is a much higher ratio of values that are predicted wrongly by the classifier logistic regression as compared to the Naïve Bayes as the ratio of wrong predicted values is much less than the logistic regression. So, overall this has been observed that the Naïve Bayes works very much better due to a higher ratio of correct predictions and is useful for real-world predictions.

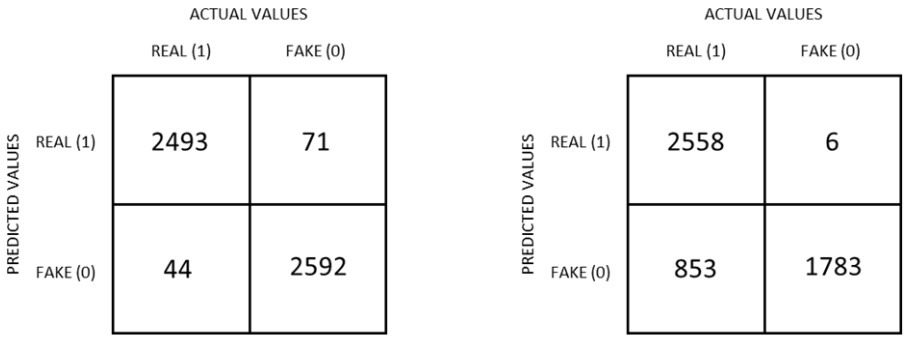


Figure 11 (a) Confusion Matrix for Naïve Bayes and Figure 11 (b) Confusion Matrix for Logistic Regression.

4.2 Comparative Analysis

When using the BERT Approach, Naïve Bayes Algorithm [58], and Logistic Regression [58] on our dataset 98% accuracy was obtained in the first cycle. The results are obtained using accuracy formula (1) that uses confusion matrix values as shown in figure 11 (a) for Naïve Byes and figure 11 (b) for Logistic Regression that includes TP, FP FN TN values. When the values are substituted in the accuracy formula (1), calculated and obtained 98% accuracy for both the Naïve Bayes as well as Logistic Regression model. However, as discussed previously due to high False Negative (FN) values the model Logistic Regression is not suitable for real- world problems for predicting fake news and hence Naïve Bayes is the best model that archives 98% accuracy and has less number of FN values and is suitable for the real world problems. Figure 12 shows the graph of the accuracy obtained in the first cycle using the Kaggle Dataset [52], using the BERT model with the Naïve Bayes and Logistic regression. The 98% accuracy was obtained in the first cycle, which is much better than the prior research work.

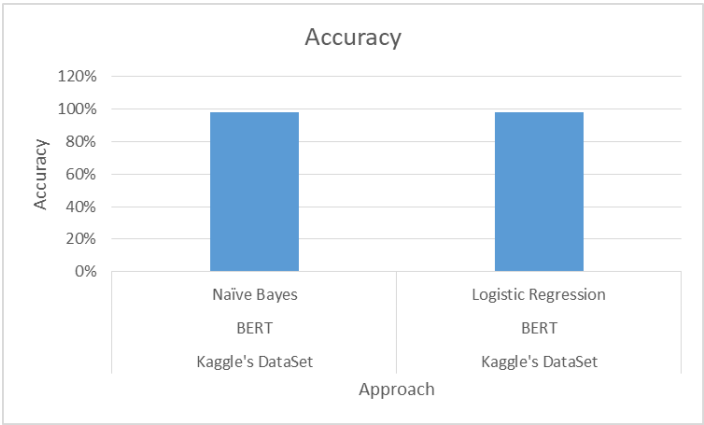


Figure 12: Obtained Accuracy

Based on the confusion matrix and the previously acquired findings, it was determined that Naïve Bayes performed better than Logistic Regression. This is because, in Logistic Regression, 853 phony news items were predicted while true news was real. This is not good in real-world scenarios or environments. Moreover, the Naïve Bayes works better than the Logistic Regression is analyzed by running the number of prediction cycles as described in the next section.

4.3 Comparative Analysis of results obtained in the prior research work

Considering Table 1 describes the comparison of the prior results obtained by various authors on the Kaggle dataset [52]. As we can see, the accuracy attained by the earlier writers is not as high as the 98% acquired in the present study. This paper aims to solve the problem of fake news and solutions to improve accuracy using BERT and machine learning classifiers. The analysis shows that previous research has relied on conventional methods, which have drawbacks not only in terms of accuracy but also in terms of contextual knowledge of the text. The prior approaches may perform well in some areas however, if we consider the real world such as in the case of context understanding scenarios these prior approaches may not perform well.

Table 1: Prior results

Author	Dataset	Vectorizer	Classification Model	Accuracy
Anjali B, et al. [50]	Kaggle	Doc2Vec	Naïve Bayes	72%
			Neural Network	90%
			LSTM	92%
Kaliyar, et al. [26]	Kaggle	TF-IDF	Naïve Bayes	72.50%
			Ligistic Regression	69%
Singh [51]	Kaggle	Word2Vec	ANN	70.06%
			CNN	79.29%
			RNN	69.55%
Ahuja, et al. 2020 [36]	Kaggle	_	S-HAN	93.63%
Proposed Method	Fake News	BERT	Naïve Byes	98%
			Logistic Regression	98%

4.4 Unique Predictions Cycle

The unique prediction cycle analysis is also carried out utilizing the Naïve Bayes Algorithm [58] and Logistic Regression [58] in the BERT method. In this analysis, we made adjustments to the algorithm to make it run continuously and provide unique predictions each time training and testing are carried out. This will offer us the opportunity to identify various expected results utilizing a natural language approach and a machine learning method. This analysis is performed unless we do not obtain the constant accuracy, as soon the constant accuracy is received the program stops automatically and final accuracy is obtained. This method can also work in real life when the user inputs new text the model automatically performs the training task. Figure 13 shows the unique predictions each time training and testing on the Naïve Bayes algorithm. It represents the cycle which means how many cycles the model runs to predict the accuracy on each cycle and accuracy on each cycle. We run 10 cycles for predictions (it can also be more than 10 but not limited to 10). It is clear that in the beginning, we achieved 98% accuracy and by performing continuous training the accuracy keeps on increasing, achieving a maximum of 98.70% accuracy, so the Naïve Bayes cross 98% accuracy and accuracy keeps on increasing and becomes constant at 98.7% during the continuous training of the model. There will be more chances of achieving more accuracy when more cycles are performed.

Figure 14, shows the unique predictions each time training and testing on the Logistic Regression algorithm. It represents the cycle which means how many cycles the model runs to predict the accuracy on each cycle and accuracy on each cycle. We run a total of 10 cycles for predictions (it can also be more than 10 but not limited to 10), it is clear that in the beginning, we achieved 98% accuracy and by performing continuous training the accuracy keeps on increasing and achieved maximum 98.40% accuracy, so the Logistic Regression cross 98% accuracy after three cycles, the accuracy increase fast after the third cycle and increases the accuracy but not frequently and keeps constant at 98.4% and 98.3% after the seventh cycle this shows that the Naïve Bayes works better and Naïve Bayes can also work better on large dataset too.

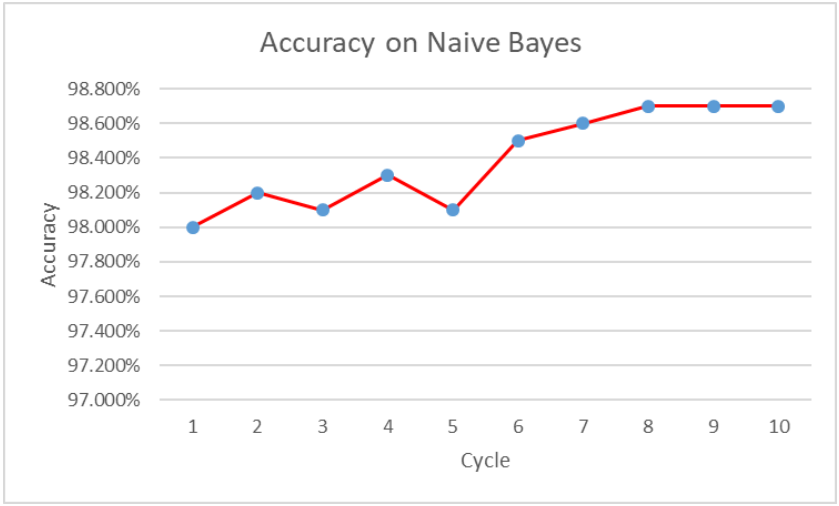


Figure 13: Unique predictions on Naïve Bayes

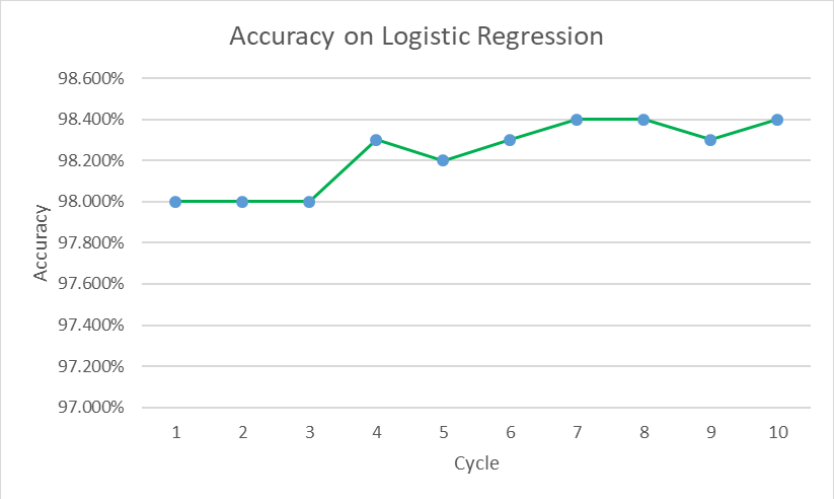


Figure 14: Unique Predictions on Logistic Regression

USER INTERFACE OF FAKE NEWS IDENTIFICATION SYSTEM

As was already indicated, this research also develops a user interface for detecting fake news using the model's analysis. The next task is to develop the proposed technique for detecting bogus news that will automatically detect the news article by providing inputs to the system depicts in figure 15 (i.e. software, a user interface in the form of a website, mobile application, or any other native software), the inputs contain the Title/Headline, Author/Source, and News Article. This system frontend is also responsive and is developed using HTML, and Bootstrap such that frontend users can easily use this system to detect the news even by using their mobile devices, tablets, or other devices depicts in figure 16. The responsive system means that the system can work on all devices and can able to adjust their display (or screen) size and viewports when the device widths get changed. The responsive design can automatically hide, resize, enlarge, and shrink a user interface to allow the user interface to look good on all device widths. It contains the simple form having three inputs (i.e. Title/Headline, Author/Source, and News Article). Upon receiving the provided inputs from the end-user, the fake news detection system will indicate if the news contributed is fake or real. If the news is fraudulent, the output will be marked as such; if it is true, it will be marked as such. This fake detection system works very differently at the backend. At the backend, the fake news detection system uses the classification algorithm and BERT approach as discussed above. Much prior research was performed where there were good solutions provided however, those solutions were in terms of accuracy not according to the end product that can used by the front-end users. So, the goal of this study is not only to improve the accuracy but also to provide an end product where front- end users can able to use the product based on their needs. The user interface can be re-designed based on the user or the organization's needs. Given below is an example of how the fake news detection system will work.

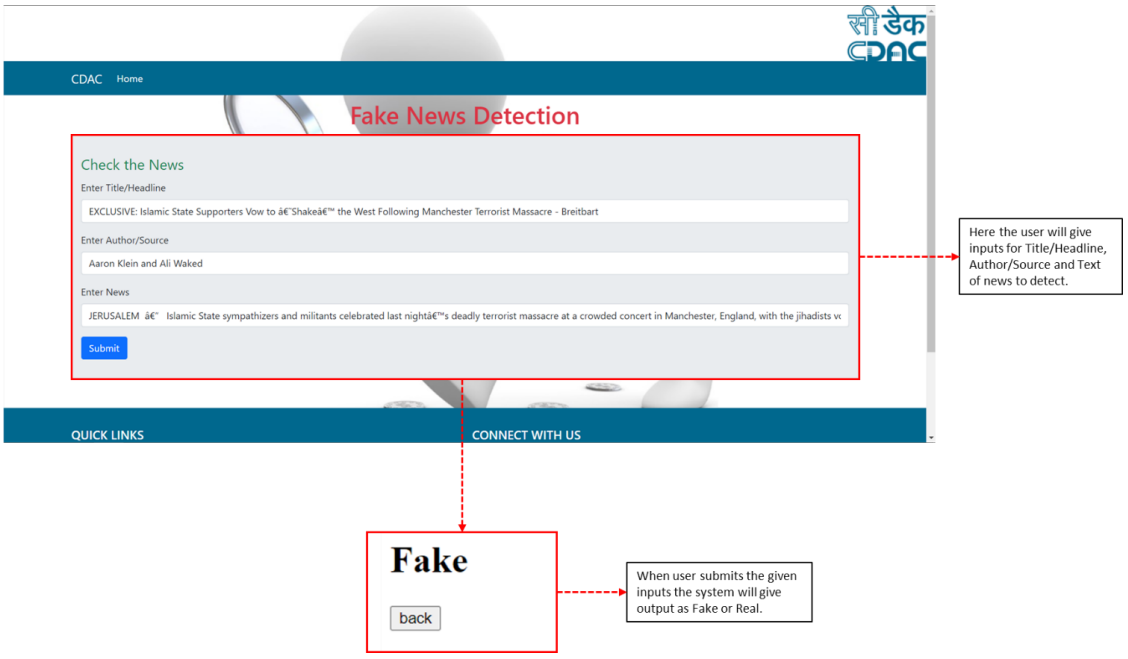


Figure 15: Fake News Identification System Interface

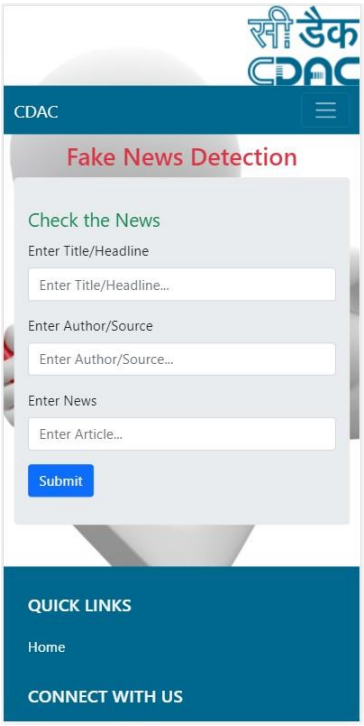


Figure 16: Mobile responsive view of the proposed system

5.1 Fake News Identification System Backend Architecture

Concerning Fig. 17 describes a backend architecture of fake news detection system 100 for Fig. 15 and Fig. 16. System 100 includes wireless devices 101, and 102 that can any client ends devices such as laptops, computers, mobile phones, PDA devices, smartphones, tablets, etc. The wireless devices 101 and 102 are connected to server 104 for transmitting a response to wireless devices 101, and 102 and receiving requests from wireless devices 101, and 102. Server 104 can be any kind of server that is located anywhere in the network such as it can be any local LAN server, cloud server, any client device having server functionality, etc. Server 104 runs the BERT model, classification algorithms, and programs based on the received request to detect fake and real news. The wireless devices 101, and 102 connected to server 104 via network 103. The network can be a local LAN network such as a Wi-Fi network, a virtual private network (VPN), a cloud network, the internet, etc. The wireless devices 101, and 102 displays a responsive user interface for detecting fake news or real news as shown in Fig. 15 and Fig. 16. The user uses wireless device 101, and 102 and sends a request 105 from their wireless device 101, 102 to the server 104 via a network 103 for detecting fake news or real news. Wireless devices 101, and 102 can be installed with the native application; it can be a web application that can run on the device's web browser. The server receives requests 106 from wireless devices 101, and 102 via network 103. Server 104 receives text having title, source, and news content from the user as shown in Fig. 15 and Fig. 16. The Server 104 preprocess the text received and applies the BERT model and classification model to identify results such as fake or real. Server 104 transmits a response 106 to wireless devices 101, and 102 via network 103. The wireless devices 101 and 102 receive response 105 from the server and display results such as Fake or real see Fig. 16 on the wireless devices 101, and 102 based on the user request.

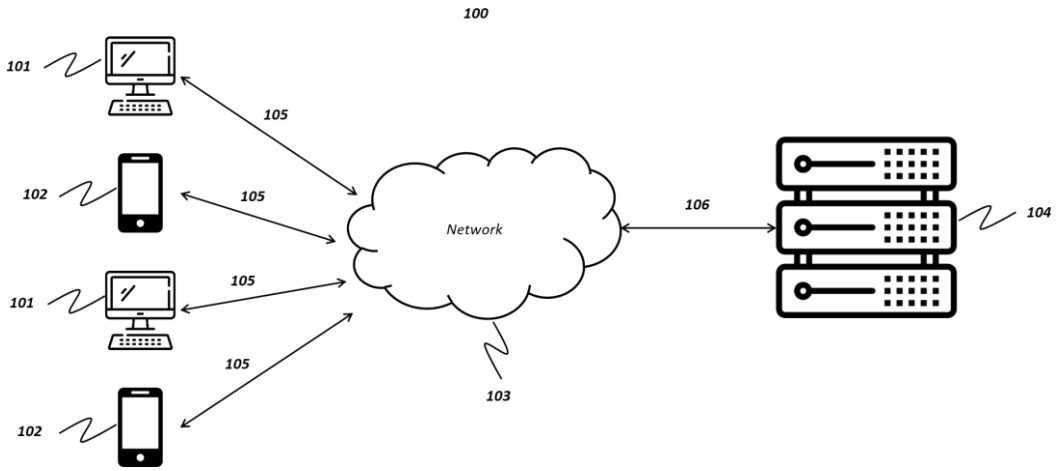


Figure 17: Fake news detection backend architecture

This research is merely a modest attempt to meet the demand for identifying false material that circulates on social media and various news websites. Several user-friendly and advanced approaches and techniques have also been adopted. This study might be able to effectively identify fake news, articles, and information distributed across the internet via blogs and social media. The objective of this fake news detection system is to provide an interface that enables the users and researchers to make reasonable detection of fake news made within a limited time frame at the beginning of this project, the BERT model will be applied, and machine learning approaches and techniques will be used to make it more powerful and useful. This research explains the issue of

identifying fake news and offers a solution for doing so accurately using the BERT NLP approach. The accuracy is calculated using the Nave Bayes and Logistic Regression algorithm, and a front-end interface is provided to allow users to quickly determine whether a piece of news is fake or not. A larger dataset (more than 20800 rows in this paper) can be used to detect fake news in a real environment, with the analysis being done with high-performance systems (HPC) to process the huge data using the BERT NLP approach. More machine-learning algorithms can be utilized in the future to discern between genuine and fraudulent news. The future scope of this research will include an analysis of real-time datasets such as the Facebook and Twitter datasets. Using powerful Artificial Intelligence and machine learning algorithms to distinguish between fake and true news in real-time circumstances. More machine-learning algorithms can be used in the future to distinguish between real and fake news. The future scope of this research will include the analysis of the real-time dataset such as Facebook, and Twitter Dataset. Using more advanced Artificial Intelligence and machine learning models to identify fake and real news in real-time scenarios.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to the Centre for Development of Advanced Computing (C-DAC), Noida, for providing the necessary academic environment and resources to support this research titled “Improving Fake News Detection Technique with BERT.”

Varun, an M.Tech student in Information Technology at C-DAC Noida, extends his sincere thanks to Mr. Rahul Mishra, Assistant Professor at C-DAC Noida, for his valuable guidance, constructive suggestions, and encouragement throughout the research process. His insights and support have contributed significantly to the development and refinement of this work.

The authors also acknowledge the contributions of researchers whose published studies on fake news detection, natural language processing, and Bidirectional Encoder Representations from Transformers (BERT) have provided a valuable foundation for this research. Finally, the authors express their appreciation to everyone who directly or indirectly contributed to the completion of this paper.

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