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An Innovative Approach for Fake News Detection Using Machine Learning

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Abstract

This research aims to increase people's awareness of fake news on online social networks and help them determine the reliability of the information they consume. It investigates methods for detecting fake news sources, authors, and subjects on online social networks. The project uses an open-source online dataset of fake and real news to determine the credibility of news. Various text feature extraction techniques and classification algorithms are reviewed, with the Support Vector Machine (SVM) linear classification algorithm using TF-IDF feature extraction achieving the highest accuracy of 99.36%. Random Forest (RF) and Naive Bayes (NB) had accuracy scores of 98.25% and 94.74%, respectively.

Index Terms: *Artificial Intelligence, Fake News, Machine Learning Algorithms, Natural Language Process, Support Vector Machine.*

I. INTRODUCTION

The growth of data production has led to an increase in fake news, where inaccurate information is spread intentionally to advance certain agendas. Fake news can have a significant global impact because of the vast user base of online social networks, where fake news can spread quickly and easily. The process of detecting fake news is challenging due to the difficulty in identifying the authors and topics of fake news, as well as the need for time-consuming evidence-gathering and fact-checking [1]. The authors and subjects of fake news can be obtained through social network websites or external knowledge repositories, which can provide information for background checks. The credibility of news articles is linked to the reliability of their sources and subjects. In this paper, "fake news" refers to false news articles, creators, and subjects [2].

Fake news is categorized into five types according to literature: (1) Deliberate Disinformation, (2) Click-Bait, (3) Fake Websites, (4) Satirical Articles, and (5) Hoaxes [3]. Deliberate disinformation refers to spreading false information with the intent to mislead. Click-bait is information that draws readers in with the intention of getting them to click on false information. Fake websites make money by generating a flood of advertisements. Satirical articles, such as "The Onion," often spread false information in a humorous way. Hoaxes are false information that harm and financially depletes its consumers [4].

False news on social media is a major concern with potentially serious impacts such as impacting national security, altering public opinion, and influencing elections. It is challenging to identify due to cognitive biases and the echo chamber effect [5-7]. The proposed research aims to tackle the issue of false news on social media by developing a model to differentiate between false and authentic news through Natural Language Process (NLP), and machine learning algorithms {Naive Bayes (NB), Support Vector Machine (SVM), and Random Forest (RF)}. The goal is to help news consumers detect false information by creating a tracking and reporting system for fake news. The significance of the project is to raise awareness about online news and improve critical evaluation, preventing the spread of false and misleading information. The study will evaluate the algorithms using a new dataset.

An article discusses the impact of globalization and online platforms on information exchange, including the propagation of false news on social media [8]. The article proposes a machine learning-based approach to identify both fake and genuine news using the sklearn module, TF-IDF vectorizer, and different ML models such as Passive Aggressive Classifier, Naïve Bayes algorithm, Logistic Regression, Decision Tree, Long Short Term Memory (LSTM), and Bidirectional Encoder Representations from Transformers (BERT). The accuracy score and confusion matrix, are used to evaluate the performance of the model, and user input can be used to determine whether news is fake or real.

Fake news has serious consequences, including impacting national security and swaying people's opinions and election outcomes. People tend to prefer news that aligns with their beliefs, which can lead to consuming fake news, but cognitive biases and the social media echo chamber can make it difficult to detect and correct misinformation [5]. The spread of fake news can further polarize public opinion and highlights the need for objective fake news identification systems. Fact-checking may not be enough to reduce the risk of incorrect information consumption and information polarization.

II. STATE OF THE ART

The effectiveness of fake news identification requires trustworthy veracity evaluation methodologies due to the difficulties in identifying misleading language and other indications in controversial content on social media. The majority of current research on fake news detection is based on deception detection methods. A unique ML fake news detection method was proposed by researchers which outperforms other methods and achieves an accuracy of 78.8% [9]. The method was tested in a real-world application within a Facebook Messenger Chatbot, achieving an accuracy of 81.7% in detecting fake news. The final dataset used consisted of 15,500 posts from 32 sites with more than 2,300,000 likes and 900,000 users, with 42.4% being non-hoaxes and 57.6% being hoaxes.

A Study achieved a 74% classification accuracy using a dataset of Facebook news posts with an NB classifier [10]. Study [11] also achieved 74% accuracy using an NB classifier but with lower accuracy due to ignoring punctuation errors.

A study [12] attempted to use an NB classifier to identify false news on Facebook and Twitter, but accuracy was low due to the lack of legitimacy of the material on the platform. The authors presented a machine learning framework to address issues such as low accuracy and slow processing time in handling hundreds of tweets per second [13]. They gathered 400k tweets, including 150k spam and 250k non-spam, and derived lightweight characteristics and top-30 informative words. The framework outperformed existing solutions by 18% and achieved an accuracy of 91.65%.

A study analyzed Twitter content using the BuzzFeed fake news dataset and identified features that are most predictive for accuracy evaluations [14]. This method is limited to a small percentage of Twitter conversation threads as it can only be used on trending tweets.

The second method studied various supervised learning methods and reviewed the decision tree method [15]. Decision trees are simple, fast, and can handle both categorical and numerical data, but may result in a complex tree structure and become an unstable model in certain situations.

This research aims to provide insight into the characterization of news stories in the current era and analyze their effects on readers through the examination of various news content categories. It explores existing methods for fake news detection that rely on text-based analysis and discusses well-known datasets.

The work concludes by highlighting four important open research issues that could guide future research and provides a theoretical approach to identifying fake news by examining psychological variables as shown in Table I.

Table I: Related Works

S. No	Author	Advantages	Disadvantages	NV	SVM	RF	Others
1	[9]	Evaluated a software system using the Facebook dataset.	The chosen dataset was skewness and has only 4.9% of fake news. Worse fake news classification accuracy of 74% only.	X			
2	[10]	A technique for detecting fake news was developed as a software framework and tested on Facebook records with an accuracy of 74%.	Low accuracy since the punctuation mistakes in the document, were ignored.		X	X	X
3	[11]	Build a classifier to explain how to integrate fake news detection into several social media platforms.	Low percent of accuracy since the collected date information lacks total reliability.	X			
4	[12]	Provides a framework to address various issues in fake news detection, including low accuracy, a time lag of BotMaker, and the slow processing time for handling large numbers of tweets in real-time.	Since the Twitter API is open to all users, spammers may change their behavior as time passes, which might affect the matrix records.		X	X	X
5	[13]	Describes a method for automating fake news detection on Twitter using machine learning. It analyzes Twitter content with a focus on accuracy ratings from journalism and crowdsourcing and identifies the most predictive features through feature analysis.	The fake news detection technique has limitations and can only be applied to a limited percentage of Twitter conversation threads as most tweets are not widely retweeted.				X
6	[14]	Analyzed numerous supervised learning algorithms and covered decision trees' benefits and drawbacks.	In some cases, this approach may result in a complex tree structure, making it a very unstable model.		X		

The European Union has launched initiatives to study fake news and raise awareness and media literacy as one of its pillars. This could benefit data protection as media-literate consumers are more cautious when disclosing personal information. Effective fake news detection could also reduce defamation of individuals who are often falsely accused of spreading fake news through accounts used to hide the origin of the fake news. The technology for detecting fake news would limit such defamation as fake news is often spread with the intention of harming specific people or groups [16]. To spot fake news, you can: verify the source's web URL, change your search engine, question strongly emotional material, never accept breaking news as fact, and be aware that fake news can appear in different forms. Use these tips to help distinguish truth from fiction. Combating fake news is difficult as it balances freedom of expression and media independence. Fact-checking requires knowledge and trustworthy sources due to the large volume of fake news spreading on social media. Fake news can be detected by comparing consistency with various domains, such as technical and social backgrounds. Modern fake news is a serious issue that spreads at an unprecedented rate, leading to its widespread dissemination and causing harm [17]. To prevent the spread of false information, early detection is vital. The issue of unlabeled news and the difficulty of training a large-scale model with practical constraints, such as the unavailability of domain experts and the cost of human labeling, also need to be addressed. An alternate method is to use noisy or limited sources for supervision [18].

III. METHODOLOGY

The section discusses our research project methodology, which involves using empirical and iterative methods to better understand a specific topic. We start by doing library research and writing a literature review to gain a deeper understanding of the subject and relevant debates. We then develop a rough plan for our project, which involves using machine learning algorithms to conduct simulations. We face challenges along the way, including unexpected issues and difficulty in choosing the best algorithms for our project. However, we persevere and continue to work on our project by using simulation techniques to experiment and improve our learning.

The article's goal is to identify fake news by using a multi-source news dataset and the social contexts of social media users. The problem of detecting fake news is formally stated below:

- Input: news articles, social contexts, and related site data.
- Output: Either the label "fake" or "real," depending on the input.

The proposed framework for fake news identification starts by collecting news from real-world sources, which is referred to as the dataset (input). In the preprocessing component, the news content is included and each news item is labeled as real or fake as shown in figure I.

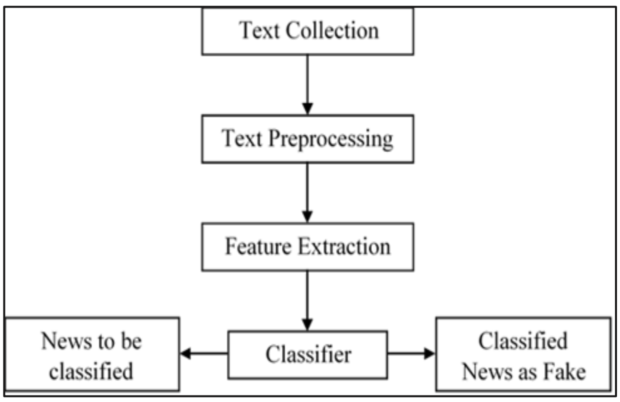

Figure I: Overview of the Proposed Framework

The methodology includes the following steps:

- Dataset and Text Preprocessing: In this step, an open source and freely available online ISOT Fake News dataset is used, which contains both fake and real news CSV files that were collected from multiple domains. Pre-processing processes include data cleansing, stop words removal, tokenization, and stemming to improve the performance of the dataset.
- Tools Selection: Python 3.10.5 is used along with various libraries such as Numpy, Pandas, and Sklearn. Machine learning classification methods are also used.
- Machine Learning: The use of Machine Learning (ML) methods is discussed to create a classifier for fake news detection. The process involves two stages; training and testing. In the training stage, the algorithm is trained on a collection of categorized data to predict or classify new data. In the testing stage, a portion of the classified dataset is used to evaluate the classifier's performance, with 20% of the dataset typically used for testing and 80% used for training the algorithm.
- Classifiers Description: Multiple classifiers are implemented in the study, including Naïve Bayes (NB), Support Vector Machine (SVM), and Random Forest (RF). Each classifier is trained using a training dataset and evaluated using accuracy, precision, recall, and F1 score metrics.

The proposed framework aims to identify fake news by analyzing news articles, social contexts, and related site data. The output of the framework is having a label of "fake" or "real" depending on the input. The methodology uses iterative processes and simulations to experiment and improve learning, despite challenges such as unexpected issues and difficulties in selecting the best algorithms.

A. Dataset and Text Pre-processing

In this work, an open-source and freely available online ISOT Fake News dataset is used, which contains both fake and real news CSV files that were collected from multiple domains [19].

Since machines cannot read text, raw text must be translated into numbers before being utilized as training data. Data manipulation or cleaning done prior to use in order to improve performance is referred to as preprocessing.

Pre-processing processes also include as shown in figure II:

- Data Cleansing: The process of removing null, pointless, improperly structured, noisy, or incomplete data from a dataset is known as data cleaning. Having clean data will boost productivity in general.
- Stop Words Removal: Stop Words are the often used words that have no bearing on the overall outcome and can be ignored prior to training.
- Tokenization: Tokenization is a process in NLP that breaks down paragraphs and sentences into smaller parts for easier meaning assignment.
- Stemming: Stemming is the process of stripping tokens of their suffixes to return them to their original root form. For instance, texting is the token that will be changed to "text" and "ing" will be eliminated.

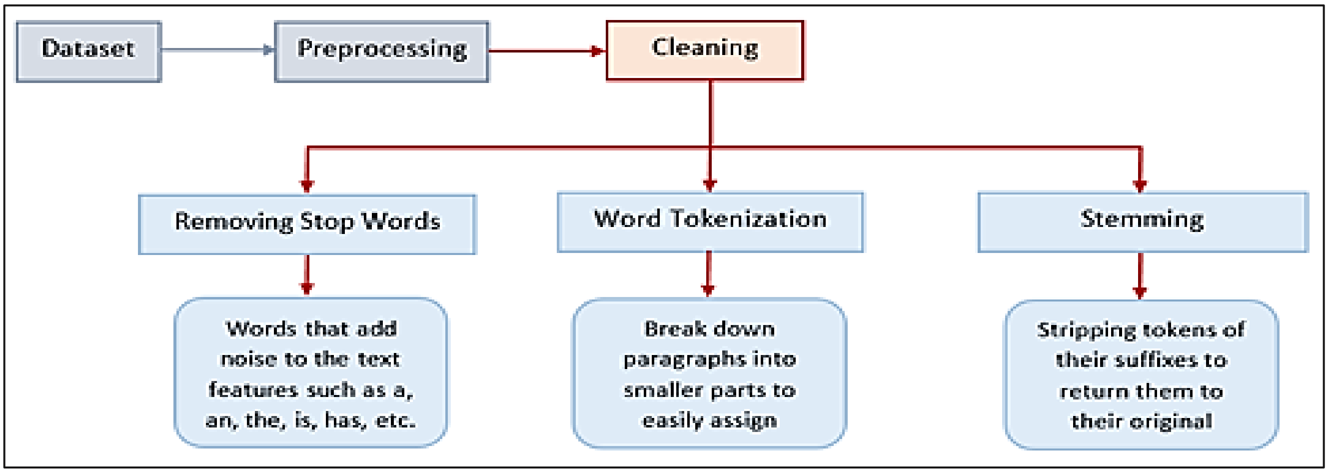

Figure II: Dataset Cleansing Process

B. Tools Selection

The selection tools are as follows:

- Python - 3.10.5.
- ISOT Fake and Real News Data Set [19].
- Machine Learning (ML) Classification Methods.
- Numpy.
- Pandas.
- Sklearn.

C. Machine Learning

The Section discusses the use of Machine Learning (ML) methods to create a classifier for fake news detection. The process involves two stages: training and testing. In the training stage, the algorithm is trained on a collection of categorized data to predict or classify new data. In the testing stage, a portion of the classified data set is used to evaluate the classifier's performance, with 20% of the data set typically used for testing and 80% used for training the algorithm.

D. Classifiers Description

The classifiers were trained using a training dataset and evaluated using accuracy, precision, recall, and F1-score metrics.
Multiple classifiers were implemented in the study:

a) Naïve Bayes (NB):

NB is a powerful classification model that performs well with small datasets and uses less storage space. However, if words are closely connected, they may not lead to good results. It is based on Bayes theory and assumes independence between predictors.
The probability of an attribute belonging to a class, independent of other classes, is explained by the NB formula in eq. (1) and explained in eq. (2):

$$P(c|X) = \frac{P(x|c)PI}{P(x)} \quad (1)$$

$$(c|X) = (x1|c)\times(x2|)\times\ldots\times(x2|c)\times P(c) \quad (2)$$

Where:
P (c|X) = The Posterior Probability.
P(x|c) = the Likelihood.
PI = the Class Prior Probability.
P(x) = the Predictor Prior Probability.

b) Support Vector Machine:

Support Vector Machine (SVM) is a binary classification model that uses hyperplanes in an N-dimensional space to separate data points into two classes. Its goal is to find the hyperplane with the largest margin to increase accuracy. SVM is known for its fast learning speed, high accuracy, and ability to handle irrelevant features. It has been successful in detecting fake news and its cost function is represented mathematically as can be seen in eq. (1), eq. (2), and eq. (3) respectively [20], and [6].

$$J(\theta) = \frac{1}{2}\sum_{j=1}^{n}\theta^2 j \quad (3)$$

Such that, $$\theta^T x^i \geq 1, \quad y^i = 1, \quad (4)$$

$$\theta^T x^i \leq -1, \quad y^i = 0 \quad (5)$$

The above function employs a linear kernel. Kernels are typically used to fit multidimensional or difficult to simply separate data points. We have applied kernel SVM (Polynomial SVM) model in this scenario.

c) Random Forest (RF)

It is a classification technique that uses multiple decision trees for accurate prediction. The prediction is made by combining the results of many trees through bagging and feature randomization, with the class receiving the most votes being the prediction. RF is reliable as it eliminates overfitting through averaging predictions and has high accuracy from a large number of trees.
The optimal model was trained using grid search with various parameters and the Gini index was used as a cost function to estimate splits in the dataset, see eq. (6) [21].

$$G_{ind} = 1 - \sum_{i=1}^{c}(P_i)^2 \quad (6)$$

E. Performance Matrix

A confusion matrix was used as the basis for evaluating the effectiveness of algorithms. It includes 4 parameters (true positive, false positive, true negative, false negative) to represent the performance of a classification model on the test set.

IV. PROPOSED MODEL DESIGN

This section describes a method for identifying fake news using NLP techniques. It involves collecting a dataset of both fake and real news, cleaning and preprocessing the text data, dividing the data into training and testing sets, and using NB, SVM, and RF classifiers to analyze the data. The accuracy of the models is tested through experiments, and the final fake news detection model is presented. The methodology is depicted in figure III.

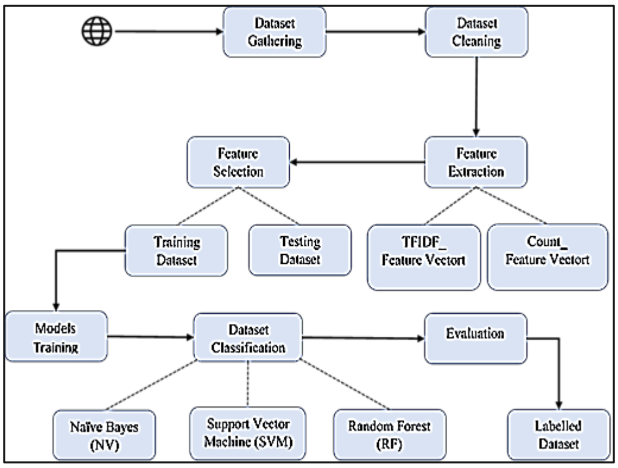

Figure III: Model Building Design

The framework for detecting fake news consists of three modules: data collection [22], pre-processing, and clustering. The data is collected from reliable news websites using a custom web crawler and then processed through text-processing algorithms to extract topics and events. The classification module separates the news into two categories, fake or real, and integrates both the training and testing process.

A. Design a Framework

The project design includes an overview structure that explains the various components used in the project, including objects, methods, functions, classifiers, and algorithms.

B. Data Exploration

The classification dataset for the project was from a public-domain source and includes both real and fake news articles [6].

C. Natural Language Processing for Text Preprocessing

It is a subset of AI that aims to make sense of unstructured data such as electronic conversations. NLP breaks down the language into smaller pieces, understands the relationships between these pieces, and combines them to form meaning. NLP methodologies range from statistical and machine learning to rules-based and algorithmic approaches. The use of deep learning and algorithms is crucial for NLP to analyze and understand human language and sometimes predict human intention. By transforming unstructured text data into structured and meaningful insights, NLP can accurately index data and categorize it into different groups.

There may be additional phases added to the NLP classification process:

- Cleaning: Data cleaning refers to the process of correcting or removing any inaccurate, incomplete, irrelevant, duplicate, or improperly formatted data in preparation for analysis.
- Tokenization: This divides the text into single phrases or semantic units.
- Stop Word Removal: Eliminating words that don't offer any initial data, including prepositions and articles.
- Lemmatization and Stemming: Reducing words to their most basic forms while analyzing word context.

D. Feature Extraction

This research aims to implement a detection system for fake news based on the textual content of news articles. The initial stage is text feature extraction to reduce redundant data and speed up the machine learning process. Three different feature extraction techniques, Word Embedding, Count Vectorizer, and TF-IDF Vectorizer, will be used in the project.

E. Dataset Classifiers

The author decided to use NB, SVM, and RF algorithms as text classifiers to classify the dataset into fake or real news articles due to their high accuracy percentage.

F. Coding

The coding process involves importing libraries, uploading news datasets in CSV format, reading and cleaning the data by checking for null values and dropping unneeded columns, analyzing the distribution of fake and real news, combining title and text columns, visualizing the news using word clouds, preprocessing the news text using NLP, implementing feature extractors, splitting the dataset into train and test sets, running classifiers (NB, SVM, Random Forest) on the training dataset, making predictions on the test dataset, and creating a data frame to compare the performance of all classifiers.

G. Simulation

The author conducted a simulation to evaluate the accuracy and effectiveness of their proposed methods for classifying news articles as fake or real. The simulation started with collecting and preprocessing the dataset, implementing feature extraction, and running multiple classifiers. The author then compared the results to determine the success of the project. The simulation outcome demonstrated success and met the objectives, as shown in the study strategy in figure IV.

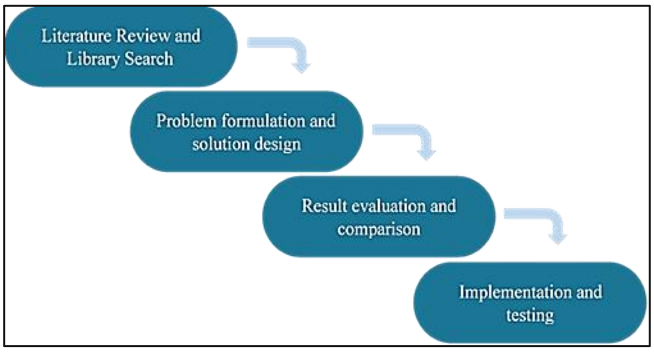

Figure IV: Phases of the Project

H. NLP Models

Feature reduction is performed to improve the accuracy and performance of the classifier by removing irrelevant and redundant features in the dataset. This is achieved by limiting the text feature size and focusing only on words that appear a certain number of times and by using machine learning methods such as CountVectorizer and TF-IDF to improve the efficiency of the process.

The pre-processing steps involved in feature reduction include the 'n' number of used words, lowercase conversion, and stop word removal.

- CountVectorizer: This approach calculates the frequency of each word in the text, orders the results, and selects the most frequent features using the max features hyperparameter. Despite its convenience, this method often yields biased results, potentially overlooking important but less common features.
- TFIDFVectorizer: Term Frequency Inverse Document Frequency (TFIDF) is used to turn text documents into vectors depending on the relevance of the words. The matrix that is created contains data on the least and most relevant terms or words in the document and is based on the bag of words model.

I. Classification Sequence

Machine learning classifiers are taught to recognize fake news stories. Only valuable information should be included in the training dataset for these classifiers. The training process for a classifier is shown in the table in the training dataset. A classifier is then utilized for experiments after the training as shown in table II.

Table II: Classifiers Training Process

Dataset
⇩ Removing Stop Words or Stemming
⇩ Test Dataset and Training Dataset
⇩ Training Classifier
⇩ Experimental Results

J. Coding Sequence

Model Building Coding Sequence is shown in table III.

Table III: Classifiers Training Process

Algorithm	
Input	**News Content**
1.	Convert text to lowercase
2.	Remove punctuations, digits, and stop words from the text
3.	**Repeat:** Input: Receive each news article Calculate the count vector for it Append the count vector to the count_feature vector Until the end of the news article
4.	**Repeat:** Input: Receive each news article Calculate the TF-IDF vector for it Append the count vector to tfidf_feature vector Until the end of the news article
5.	Parse count_feature vector and tfidf_feature vector into the classifier The return feature vector gives us the highest accuracy
6.	Build a model with the feature vector
7.	Implement NB Model
8.	Implement SVM Model
9.	Implement RF Model
Output	**Predict the Label of News---Fake or Real**

V. RESULT AND DISCUSSION

In this research, the ISOT Fake News Dataset was used, which is an open-source and freely available dataset that contains both fake and real news articles in CSV files collected from multiple sources. The Fake News Dataset has 23481 rows and 4 columns, while the Real News Dataset has 21417 rows and 4 columns [6]. The news articles are composed of the main content (news body) and side information, including title, text, subject, and date of publication. The datasets were used to differentiate between real news articles that accurately describe real-world events and fake news articles containing false claims.

The dataset consists of two CSV files with over 12,600 articles in each file, including details such as the title, text, type, and publication date. The articles were collected from 2016 to 2017 and were cleaned and processed, but some errors from the fake news file were not removed from the text. The dataset includes a variety of topics, mostly about politics and world news. A breakdown of the categories and the number of articles in each category can be found in the following table IV.

Table IV: Breakdown of the Article's Categories and Number per Category

News	**Size (Number of Articles)**	**Subjects**	
Real News	21417	**News Type**	**Articles Size**
		World	10145
		Politics	11272
Fake News	23481	**News Type**	**Articles Size**
		Government	1570
		Middle east	778
		US	783
		Left	4459
		Politics	6841
		News	9050

The study utilizes NLP as a tool in Python, using libraries such as PANDAS and NLTK for data analysis and text processing. The goal is to create a model using TF-IDF and count vectorization for the binary classification task of detecting fake news. The study focuses on improving the accuracy of fake news detection by determining relevant features before classification.

A. Feature Extraction and Text Pre-processing

The study focuses on using machine learning techniques such as CountVectorizer, TFIDFVectorizer, NB, SVM, and RF classifiers to detect fake news in publicly available datasets. The text-based classification is combined with machine-based text transformation to improve fake news detection accuracy. The dataset used is pre-processed by eliminating stop words and converting the text to lower-case letters while removing any special characters that could cause anomalies in the classification process as shown in figure V.

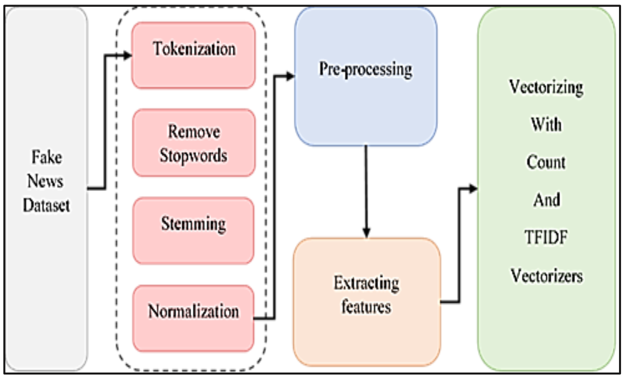

Figure V: Process of Data Cleaning; Starting with Raw Dataset until Machine Learning Models

The necessary pre-processing procedures involve the following steps as shown in figure VI:

- Gather news elements.
- Eliminating punctuation.
- Break down the news article's content into its individual words utilizing (Tokenization).
- StopWord Elimination.
- Standardizing words to use just lowercase characters by utilizing (Lemmatization).

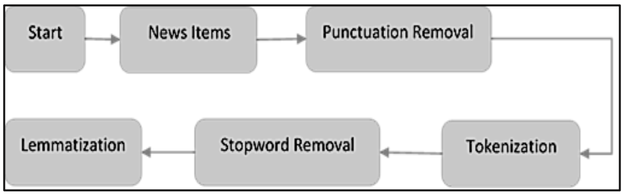

Figure VI: Steps Sequence of Text Preprocessing

B. *Performance Matrix*

The study uses a confusion matrix to evaluate the performance of the machine learning algorithms used to detect fake news. The confusion matrix shows the true and false values of the algorithm and helps to visualize the errors being produced. Other metrics are also used to assess the performance of the algorithms, but the confusion matrix is the basis of most of them.
The confusion matrix includes four parameters (true positive, false positive, true negative, false negative) to tabulate the performance of the classification model on the test set as shown in table V:

Table V: Confusion Matrix Description

Actual Value	Predicted True	Predicted False
Actual True	True Positive	False Negative
Actual False	False Positive	True Negative

a) Accuracy:
The most often used metric for measuring the percentage of accurately expected observations—whether true or false—is accuracy. To determine a model's performance correctness, the following equation i.e., eq. (7) could be used:

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

In most scenarios, a high accuracy score shows a good model, but since we are training a classification model in this case, a false positive or false negative might have negative repercussions. Likewise, if an article was classified as fake but contained real information, this can create undermine confidence. Therefore, employed three additional metrics; precision, recall, and F1-score which account for the inaccurately categorized observation.

b) Recall:
The total number of correct classifications outside of the true class is known as recall. In this case, it stands for the percentage of articles that were correctly forecasted out of all the correctly predicted articles, see eq. (8) below:

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

c) Precision:
The ratio of real positives to all events anticipated as true, on the other hand, is represented by the precision score. In this case, precision is the percent of positively predicted (true) articles out of all the articles that are labeled as true, its equation is given below, i.e., eq. (9):

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

d) F1-Score:
The precision/recall trade-off is represented by the F1-score. It figures out the harmonic mean between each pair. Therefore, it takes into consideration both false positive and false negative observations. The formula below, i.e., eq. (10), can be used to determine the F1-score:

$$F1 - score = 2\frac{Precision*Recall}{Precision+Recall} \quad (10)$$

C. *Implementation*

A bar plot shows the distribution of fake and real news, with fake news having more records and a higher bar compared to real news. Both datasets have records ranging from 21-23k, which is good for training a model as shown in figure VII.

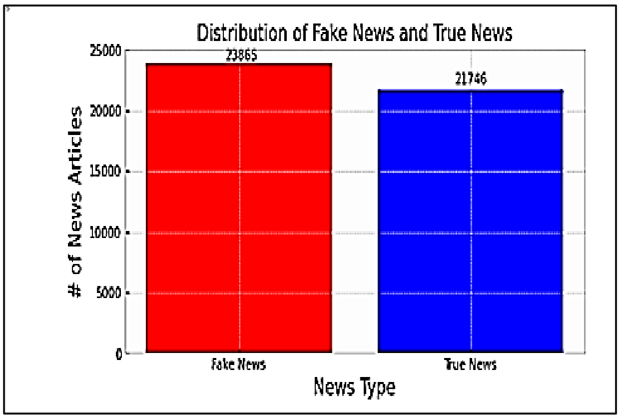

Figure VII: Distribution of Fake News and True News

A Word cloud was generated to visualize the True News dataset by highlighting the most frequently and relevant used phrases and terms as shown in figure VIII.

Figure VIII: Word Cloud of True News Frequent Phrases and Words

A Word cloud was generated to visualize the Fake news dataset by highlighting the most frequently used and relevant terms and phrases, similar to the True News Word cloud as shown in figure IX.

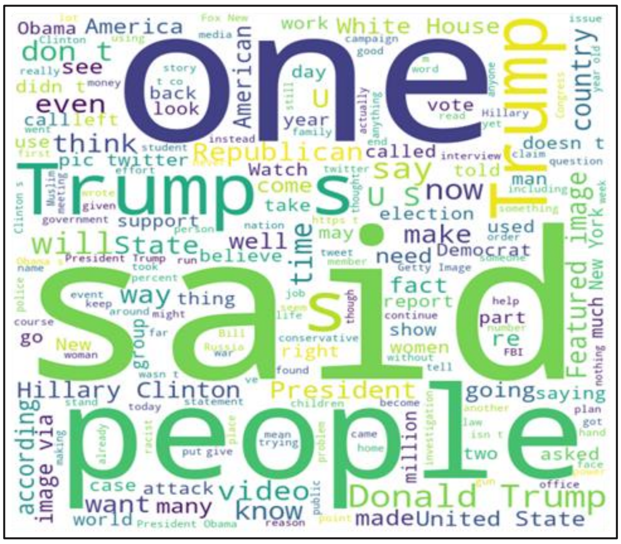

Figure IX: Word Cloud of False News Frequent Phrases and Words

The tests conducted based on the model selection and feature set combinations, showed good performance, exceeding the baseline of 0.50. SVM had the best performance when accuracy and precision were used as performance measures, but the performance of other suggested classifiers is shown in table VI.

Table VI: Performance Comparison of the Suggested Classifiers

Algorithm	**Accuracy**	**Precision**	**F1 Score**	**Recall**
RF	98.25%	98.47%	98.16%	97.85%
NB	94.74%	94.30%	94.51%.	94.72%.
SVM	99.36%	99.34%	99.33%	99.32%

When accuracy is equal in two algorithms, the F1-score should be considered as it takes into account both recall and precision, which account for false positive and false negative results. The F1-score is more useful than accuracy when the class distribution is uneven, but if false positives and false negatives have equal costs, accuracy is better. If the cost of false positives and false negatives are significantly different, both precision and recall should be included. The F1-score is calculated as the weighted average of recall and precision by taking into account both recall and precision.

When analyzing the machine learning algorithms, the specificity of the model is given greater importance than accuracy and sensitivity in the context of detecting fake news. This is because the consequences of mistaking a fake news headline as real are more serious than mistaking a real headline as fake. The results showed that the proposed system is effective in categorizing fake news and identifying important features for fake news detection. This highlights the importance of using machine learning techniques to distinguish fake and real news. The high accuracy rate of the proposed system (using SVM) shows its value and suggests the need for exploring other methods beyond basic text categorization for fake news detection. The creators of fake news often use various methods to hide their identities, making it easier for them to deceive readers. The SVM models had the highest specificity of 99.36% among the three machine learning algorithms used.

VI. CONCLUSION

The rapid spread of fake news on social media and other platforms is a major issue with potentially harmful consequences for society and the country. Early detection of fake news is a key challenge, as is the lack of labeled data for training detection models. This work proposes a new approach to fake news detection that uses data from news articles and social contexts. The approach involves analyzing fake news detection systems and traditional machine learning models to find the best, using text processing and NLP tools such as Python Scikit-Learn and textual analysis. The paper aims to develop a supervised machine-learning model that can classify fake news as true or false.

This work evaluates fake news detection methods by using three different feature extraction techniques (Word Embedding, Count Vectorizer, and TF-IDF Vectorizer) and several classification algorithms (NB, SVM, RF). The results of the confusion matrix were used to perform feature selection to determine the best features for maximum precision.

In a previous study, the majority of research used the NB method with an average prediction precision of 70-76%. Qualitative analysis, relying on sentiment analysis, titles, and word frequency repetition, was the common approach. This new strategy proposes to use textual analysis, a quantitative methodology that includes numerical statistical values as features. The addition of these features and the use of SVM, NB, and RF algorithms result in improved precision outcomes.

Table VI shows that the SVM with TF-IDF feature extraction achieves the highest accuracy among the algorithms tested, followed by RF and NB.

The study achieved its goals of using SVM Linear with TF-IDF feature extraction to classify fake news with the highest accuracy, but there is room for improvement. Future work includes building an automatic fact-checking system and incorporating more data, expertise, and techniques such as deep learning and sentiment analysis. A larger dataset may also be used for higher accuracy.

The ability to accurately detect fake news has important practical implications for various stakeholders, including media organizations, social media platforms, policymakers, and the general public. Media organizations can use fake news detection models to improve the accuracy of their reporting and reduce the risk of spreading false information. Social media platforms can use these models to identify and remove fake news from their platforms, thereby reducing the harm caused by the spread of false information.

Policymakers can also use fake news detection models to monitor and combat the spread of false information, especially during critical events such as elections and pandemics. The general public can use these models to verify the accuracy of the information they encounter on social media and other online platforms.

The proposed approach in this paper has the potential to be applied in real-world scenarios to address the problem of fake news. By using a combination of textual analysis, feature extraction techniques, and machine learning algorithms, the proposed framework achieves high accuracy in identifying fake news articles. This approach can be further refined and optimized for specific applications, such as identifying fake news related to political events or public health issues.

Another limitation is that the proposed framework relies on textual analysis alone, and does not take into account other factors that can affect the spread of fake news, such as the visual and audio elements of content. Additionally, the approach used in this study focuses on classifying individual articles as true or false but does not consider the broader context in which the articles are shared, such as the social media platform or the user demographics.

Furthermore, while the results show that the proposed framework achieves high accuracy in identifying fake news, it is important to note that the performance of the models heavily depends on the quality and quantity of data used for training and testing. In real-world scenarios, the distribution of fake news may differ from the distribution in the dataset used for training, which can affect the accuracy of the models.

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Authors Contributions

The contribution of the authors was as follows:
Maya Hisham's contribution to this study was the concept, technical implementation, data compilation, and validation. The methodology to conduct this research work was proposed by Raza Hasan along with project administration, and supervision. Data collection, correspondence, and paper writing were performed by Saqib Hussain.

Conflict of Interest

There is no conflict of interest between all the authors.

Data Availability Statement

The authors confirm that the data supporting the findings of this study are available within the article [6-19], and its supplementary materials.

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