Migration Letters

Volume: 23, No: 1 (2026), pp. 101-112

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)

www.migrationletters.com

Evaluating Supervised Learning Techniques For Accurate Fake News Identification Using Support Vector Machine Technique

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Abstract

In this era of technological advancement where the internet has revolutionised communication, users generate and share vast amounts of information, some of which is misleading and not real. Automated identification of misinformation or disinformation in textual articles poses a significant challenge. This study focused on distinguishing between fake and true news using a Support Vector Machine (SVM) Classifier trained on Term Frequency-Inverse Document Frequency (TF-IDF) vectorization method. The dataset was split into 80% for training and 20% for evaluation. Model performance was evaluated using a Confusion Matrix, Classification Report, and ROC curve. The Confusion Matrix depicted accurate predictions of 6450 fake news articles correctly classified and 215 true news misclassified as fake. Similarly, 7347 true news articles were correctly identified along with 86 fake news misclassified as true. The overall model achieved an accuracy of 97.86%Precision scores were 98.68% for fake news and 97.16% for true news, with recall scores of 96.77% for fake news and 98.84% for true news. fake news category attained an F1-score of 0.9772 while true news events attained an F1-score of 0.9799. The ROC curve, with an AUC value of 1.00, demonstrated the model's excellent diagnostic ability in distinguishing between fake and true news articles.

Keywords: *Fake News, Support Vector Machine, Classifier, Accuracy, Confusion Matrix.*

1. Introduction

In this era of advanced communication and internet facilities, propagating false information or misinformation has become convenient. The World Economic Forum (2013) identified the term "misinformation"[1] as one of the major global threats. Other terms for false information that have been identified include rumours and fake news. Fake news is false information disseminated under the guise of official news, whereas rumours are unconfirmed claims or facts without any authority. Among the things that lead to rumours include social relationships, confirmation bias, personal engagement, and source uncertainty (Muhammed & Mathew, 2022). The main purpose of doing so is often to damage someone's or an organization. reputation. Online websites and social media platforms such as Twitter, Facebook, and so on, are crowded with a plethora of information and knowing their authenticity and correctness becomes very difficult. Fake news attracts significant attention, leading people to blindly follow misinformation without reconsidering it. There are groups of people who try to take advantage of the enormous influence that mass media have on society. The use of social media has made the proliferation of fake news easy. People forwarding and commenting on such messages are responsible for spreading them further knowingly or unknowingly. Nowadays, Social bots are used to manipulate people to spread false information by focusing on super users. Another emerging technique is by using clickbait which is an advertising technique where sensational news stories as clickbait to direct viewers to adverts (de Beer & Matthee, 2020).

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Several attempts have been made to define fake news by researchers. Taking a philosophical stance, Mukherji (2018) identified fake news with the lens of Frankfurtian bullshit. According to him, the main feature of fake news includes a disregard for the truth and a desire to hide this lack of concern. He differentiated fake news from bad journalism, biased journalism, and satire, which operate within a framework of attempting to inform or entertain, the fake news is created deliberately with the purpose to mislead. Lazer et al., (2018) offered a systematic definition of Fake news which was based on organisational procedures and motives and defined Fake news as an imitation of the format of reputable news sources but lacking the editorial standards and organisational procedures required to ensure information's reliability and correctness. Wardle and Derakhshan (2017) identified three elements of fake news, although they did not explicitly use this term to discourage its usage within the political framework. These elements are the agent, message, and interpretation, and they highlighted three phases of fake news "creation, production, and diffusion."

Although fake news has existed in one or another form, it has become much more widespread in recent years, primarily centered around political issues as seen during the US presidential elections and the Covid pandemic (Bovet & Makse, 2019; Patwa et al., 2021). The term 'infodemic' was invented to represent the flooding of fake news in media and all the online platforms about COVID's causes, treatments, preventions and diagnosis techniques. The consequences of this fake news were also discussed by researchers stating that it could cause psychological problems as well as anxiety, dread, melancholy, and exhaustion (Rocha et al., 2021). Fake news impacts different segments of society. Most commonly they are created to promote specific ideologies and functions to generate strong opinions dividing the society with opposing thoughts (Olan et al., 2024). In addition, they can have financial impacts too. For example, the one tweet from 2013 announcing an "Explosion at the White House" was a rumour but reached millions of people instantly and had a significant influence precipitating a sharp decline in the stock market (Domm, 2013). This could have been prevented if there were any fake news detection tools available at that time. Several other instances demonstrate the devastating effects of fake news. In addition to the fake news that is deliberately created, there are instances where potentially true information has been denied by authorities and named as 'Fake news'. This was discussed in detail by Wang and Huang (2021) who presented some examples such as during covid pandemic when the Chinese government denied that there could be spread of a SARS-like disease and stated it be a "rumour". This had an enduring effect as it delayed people's response to health and safety emergencies, and gave other leaders the confidence to reject unpopular facts, declining press freedom and democratic standards around the globe.

2. Related Work

It becomes essential to differentiate fake news from real news. Several attempts have been made in the past to detect fake news or recognize misleading information. The study by Takahashi & Igata (2012). attempted and laid down a procedure to detect fake news or rumours using Twitter material. They suggested that the identification of bursts, retweet ratios, and word distribution differences can be used to recognize fake news. However, the variable 'retweet ratio' was better in identifying whether a rumour was spreading. Word distribution differences between rumor and correction tweets can also help detect rumours. In addition, content analysis was used to differentiate rumors from gossip or campaigns, as companies use Twitter for their campaigns (Takahashi & Igata, 2012). Since then, several other instruments have been created to identify fake news. For instance, lexical choices found in headlines and other complex language, the Twitter Crawler and the Named Entity Recognition (NER) method serve as the foundation for this procedure (Derczynski et al., 2015; Rubin et al., 2016; Atodiresei et al., 2018). The systematic review by de Beer identified five methods to recognize fake news including

- The linguistic approach where the language used by humans has used the style used by them to create stories remains peculiar exposing them. The technique utilized was Bag of Words (BOW), Semantic analysis and Deep Syntax.

- topic-agnostic approach where instead of the content the topic and design of the news item is considered. For example, flashy headlines, odd text patterns, and the inclusion or omission an author's name.
- machine learning approach in which various algorithms are used to create a dataset of verified fake news.
- knowledge-based approach which seeks to identify news before it can spread more quickly by leveraging external sources to confirm if it is true or false.
- hybrid approaches which combine machine learning and human judgement to detect false information on social media.

A recent study has been done on developing an efficient and automated framework for online false news identification to assist users in identifying relevant and worthwhile content. Machine learning can aid in creating systems with the ability to learn and carry out various tasks (Donepudi, 2019). Following the trend of successful implementation of machine learning in various domains such as precision agriculture, management sector, and biological fields (Kushwaha & Badhera, 2022; Taylor and Carrigan, 2022; Cho, 2024), text analytics using machine learning has also become very popular, particularly as a consequence of the development of massive computer power, and more efficient machine learning and statistical analysis approaches.

A recurrent neural network was used to automatically recognise rumours by Alkhodair et al. (2020) with the implementation of word embeddings. Their experiment used a real-world rumour dataset to replicate a cross-topic developing rumour detection scenario and utilized a combination of an unsupervised with a supervised learning objective. Instead of utilising a pre-defined collection of manually created regular expressions, the suggested model learnt the characteristics automatically. In order to categorise the current tweets, a sequential classifier model based on Conditional Random Fields (CRF) was used. The precision, recall and F1 values of 0.81, 0.76 and 0.78, respectively outperform other models.

Ahmad et al. (2020) used XGBoost and AdaBoost algorithms to differentiate fake news from real news by using data from the World Wide Web that covered news from various domains. The goal was to recognise the textual patterns differentiating authentic news from false pieces. Using an LIWC (Linguistic Inquiry and Word Count tool), textual characteristics were extracted from the articles which were then fed into the models. To detect fake news that was spread at the time of the Covid-pandemic, Patwa et al. (2021) used four machine learning i.e. Decision Tree, Gradient Boost, Logistic Regression and Support Vector Machine (SVM) with a linear kernel, where SVM showed the highest accuracy in detecting fake news.

The present study developed a machine-learning model to assist humans in maintaining the consistency and accuracy of online information. This has important significance because manual checking of information has its drawbacks. There can be considerable variations among the general population in identifying fake news depending on their education and socio-economic demographics. A survey conducted by Arin et al. (2023) which tested the ability of common people to identify fake news in Germany and the United Kingdom observed that respondents with higher incomes and older age groups were more skilled at spotting false news in both nations, as compared to females and leftists. Under this pretext, it is necessary to develop automatic machine-learning techniques that can empower common people as well as authorities to recognize fake news.

Motivation for this paper

In the view of expanding nature of fake news on social media and other online platforms, there is an urgent requirement to explore solutions for identifying fraudulent material on the internet as fake news. Due to the explosion of fake news, manually checking their reliability is almost impossible. Human fact-checking takes a lot of time and is prone to prejudice. Publishers, corporations and governments are facing challenges from the dissemination of manipulated narratives via bots and human propagation on the internet and they are working to minimise the ways fake news is disseminated, as well as to build technological and human systems that can filter out misleading information. Google most recently announced the launch of a brand-new online service dubbed the "Google News Initiative" to combat false information, fake news, and controversial breaking news (Tan, 2022). The purpose of this research is to investigate the efficacy of supervised learning method for the detection of false news, and attempts to make advancements in the creation of reliable instruments for preserving the accuracy of online content.

3. Material and Methods

3.1 Description of Dataset

The dataset named 'ISOT Fake News Dataset' employed in the present study was obtained from a publicly available data repository, Kaggle. It had two files, the 'Fake.csv' file contained fake articles that were scraped from various websites including topics related to Government, the Middle East, the US, political news etc., whereas the 'True.csv' file contained true news from authentic sources of Reuters. Other details of the dataset are provided below:

- Title Column- Represented the news story headlines
- Text Column- Represented the detail of the news material related to the Title
- Subject Column- Represented the news category.
- Date column- Represented the month, year, and date the news stories were published.

3.2: Procedure

The program used to analyse the dataset was Python to identify fake news using a support vector machine. The steps involved are explained in the Figure 1:

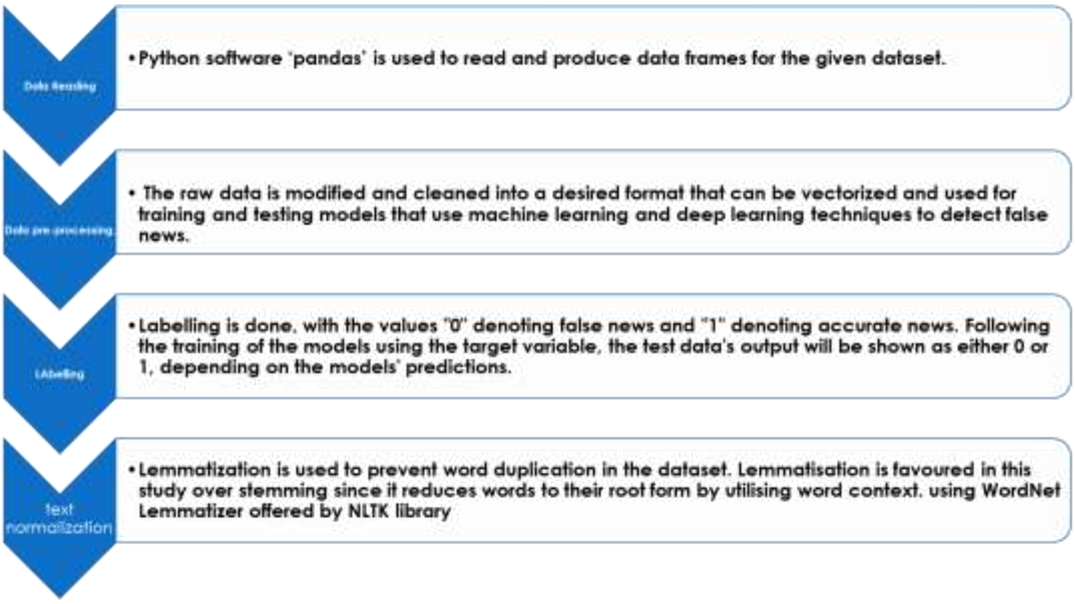

Figure 1: Steps involved in the development of a model for the detection of fake data news

3.2.1 Reading and creating dataframes: Data frames "df_fake" and "df_true" were constructed. About 23481 false news items and 21417 true news were identified.

3.2.2 Data Pre-processing: In this step, the raw data is modified and cleaned into a desired format that can be vectorized and used for training and testing models that use machine learning and deep learning techniques to detect false news. It involved:

- Empty Rows from the "text" and "title" columns in the datasets for Fake News and True News were removed. Thus, none of them are eliminated. Also, rows with invalid years and months in the "Date" column were removed.

- Unnecessary elements were eliminated. For this, a function called “data cleaning” was employed which removed texts in parenthesis, punctuation, links (https and www), words containing numbers, and HTML tags. This procedure made use of ‘stop words’ which are the most common term in the English language that has no particular or practical value in sentences. They occupy extra space in the database and can lengthen the time the models take for execution. Even after removing them, the statements' essential meaning did not change. Lowering the total vector dimensions, a necessary step in getting a dataset ready for the TF-IDF vectorizer. also breaks the dimensionality problem. With Python, the Natural Language Tool Kit (NLTK) package makes it simple to eliminate stop words.

3.2.3 Data Labelling

For this, a target variable column named ‘label’ was created, and labelling was done, with "0" as ‘false’ news and "1" for ‘true’ news. The test data result will be either 0 or 1 depending on the models' predictions after being trained using the target variable. Along with tagging, columns with names like Title and Text were combined and classified as "news" for both True and false news to improve the accuracy of detecting false news.

3.3 Normalisation (Lemmatisation)

To prepare the data for future processing, a text normalisation technique known as lemmatization was used to prevent word repetition in the dataset. Lemmatisation was favoured in this study over stemming since it reduces words to their root form by utilising word context. This method's primary goal was to eliminate word inflexion by processing words with similar meanings and returning the dictionary form of a word known as a "lemma.NLTK library's WordNet Lemmatizer is used in Python to implement lemmatization on a selected dataset. WordNet Lemmatizer searches the WordNet Database to find lemmas for words.

3.4 Feature extraction

The dataset was transformed into a format that is readable by computers since the computer is unable to comprehend the words in it. For this “Term Frequency - Inverse Document Frequency” (TF-IDF) text vectorizer was employed. The term “term frequency” (TF) describes how often a certain word appears in an article using a matrix to represent them where rows denote the number of articles and columns denote the total amount of unique words in the dataset. collection. The amount of articles in the dataset that include a certain term is known as document frequency. The word is assigned an inverse document frequency (IDF). If words appear more than once in a dataset, IDF will lower the word weight. IDF may be calculated as follows in the Mathematical Model. The IDF weight for word i in the equation is written as:

$$idf_i = log(\frac{n}{df_i}) \qquad (1)$$

where n is the total number of articles and df_i is the number of articles that make up the word i. In this case, the IDF value decreases as the DF value increases since the IDF and DF are inversely related.

The term frequency matrix and IDF weight are multiplied to determine the TF-IDF weight, as the name suggests. Within the model of mathematics.

$$w_{i,j} = tf_{i,j} \times idf_i \qquad (2)$$

Where $w_{i,j}$ is TF-IDF score for word i in article j, $tf_{i,j}$ is term frequency for word i in article j, and idf_i is IDF score for word

3.4 Model Development

This section covers the process involved in the model development for identifying false news, including data transformation, model training, testing, and performance assessment. The machine learning technique Support vector machine (SVM) was employed in this study Following data cleaning and preprocessing, the dataset was divided in the ratio of 80:20, with 80 per cent of the data used to train models and the remaining 20 per cent used to evaluate how well each model detects false news. Metrics including the Confusion Matrix, Accuracy, Precision, Recall, F1-score, and ROC Curve were computed to assess the performance of the model. Python divided the data for the model's training and testing using the "test-train split" function from the Sci-Kit package.

There are some studies that employed ML techniques for assessing the credibility of news. Support vector machines (SVM) are used to categorise authentic and fraudulent news. In SVM, two classes are differentiated by determining an optimum line or hyperplane that is at a maximum distance from each class in an N-dimensional space. There is a decision boundary called 'hyperplane' (which is a line in 2D space and a plane in 3D space) as indicated in Figure 2, that divides two classes.
The support vectors refer to the data points that are situated close to the hyperplane which influences the orientation and location of the hyperplane.
For classification purposes, SVM makes use of two concepts which are:

- Margin: It refers to the distance between the closest support vector from one of the two classes and the hyperplane. The goal of SVM is to optimise this margin to provide the best possible gap between the classes.

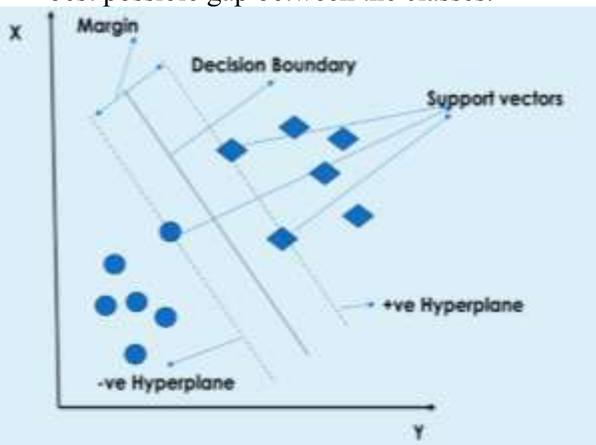

Figure 2: Support vectors for classifying two classes

In an exemplary situation of classification with two classes A and B with features x_1 and x_2, the hyperplane in 2D space is represented as

$$w_1x_1 + w_2x_2 + b = 0$$

Where w_1x_1 and w_2x_2 are the weights and b is the bias.

Maximising the margin is the SVM's goal, and it may be expressed as a convex optimisation problem:

Minimize $\frac{1}{2}\|w^2\|$
Subject to

$$y_i(w.x_i + b) \geq 1\forall_i$$

where yi is the class label of xi (+1 or -1).

Kernels: For non-linear data, SVM may perform regression and classification by using kernels which transform the data and determine the best border between potential outputs. Specifically, the technique of 'kernel trick' is used to link linearity with non-linearity. It transforms the data to a higher-dimension space by projecting the original one with a few additional characteristics.

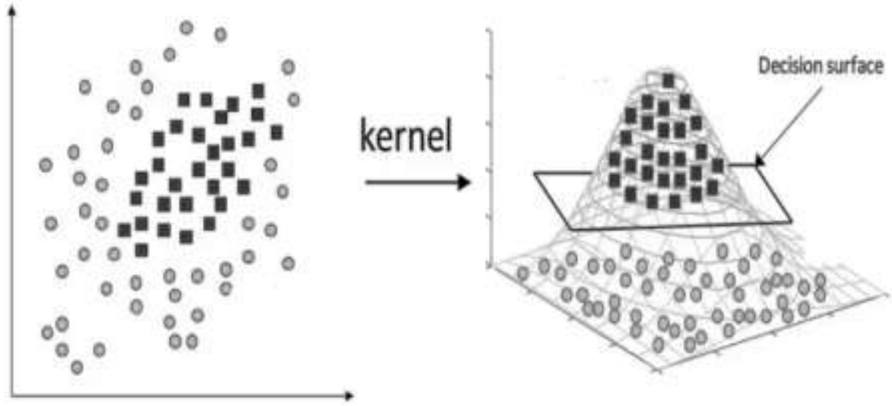

Figure 3: Kernel transformation in SVM (Nimmaturi, 2019)

3.5 Model Development

SVMs are advantageous because they are effective in high-dimensional spaces and perform well even with limited data. They are also robust to outliers in the data set. However, they can be computationally expensive to train for very large datasets.

SVM estimate a subset S of the input space from a dataset derived from an underlying probability distribution P. This subset is controlled by a predetermined parameter ν, which ranges between 0 and 1 and dictates the probability that a test point drawn from P will fall outside of S.

Regarding a certain dataset $\{x_1 \ldots\ldots\ldots\ldots x_n\}$, SVM converts the data into the feature space specified by the selected kernel. It then solves an optimisation problem to find a hyperplane that isolates the data points from the origin maximally. Here, the hyperplane which is to be find here is represented as $w.\emptyset(x) - \rho = 0$.

This can be achieved by solving optization problem such as

$$\min_{\omega,\rho,\xi} \left(\frac{1}{2}\right)^n \|w\|^2 + \frac{1}{\nu n}\sum_{i=1}^{n} \xi_i - \rho$$

subject to the constraints

$$\big(w.\emptyset(x_i)\big) \geq \rho - \xi_i, \quad \xi_i \geq 0, \qquad \forall_i = 1, \ldots, n$$

where:

- w is the weight vector,
- ρ is the offset,
- ξi are slack variables,
- ν is a parameter that controls the fraction of outliers and the margin.

3.5 Model Evaluation

How accurately the developed predicted the target label in the test dataset was used to determine the performance of the model. The task to be performed by the model in this research was to determine if the given news article was true or fraudulent. The 4 metrics used were Accuracy, Precision, Recall, and F1-score to assess the overall success rate of the model (Figure 4).

Accuracy is defined as the percentage of the number of news detected correctly (fake or real) over the total amount of news. Accuracy =

$$\frac{\text{True Positive+True Negative}}{\text{True Positive+False Positive+True Negative+False Negative}}$$

Precision tells exactly how many percentages of news are correctly predicted as real news. Precision =

$$\frac{\textit{True Positive}}{\text{True Positive+False Positive}}$$

The recall is defined as the percentage of news classified as real news even though some of the news is fake. Recall =

$$\frac{\textit{True Positive}}{\text{True Positive+False Negative}}$$

F1-score is a statistical measure of model accuracy.it is defined as the harmonic mean between Recall and Precision. F1 Score =

$$2 * \frac{\textit{Recall*Precision}}{\textit{Recall+Precision}}$$

Figure 4: Evaluation metrics for assessing model's performance

In addition, the confusion matrix was used to compare projected values with the actual value. In addition, the Receiver Operator Characteristic Curve (ROC Curve) was plotted to assess the model's efficiency.

Confusion Matrix: A 2 x 2 matrix called the confusion matrix shows the model's performance in terms of true positives, true negatives, false positives, and false negatives. When the training model correctly predicts the actual news, it is said to be a true positive. A False Positive occurs when the model that has been trained incorrectly interprets false news as real. The True Negative refers to the correct identification of no fake news. And lastly, False Negative refers to the identification of true news as fake news. All these data are provided in the form of a matrix as shown in Table 1.

Table 1: Confusion matrix

ACTUAL CASES

PREDICTED CLASSES

	Fake News	**Real News**
Fake News	True Positive	False Negative
Actual News	False Positive	True Negative
	TPR=TP/TP+FN	FPR=TN/TN+FP

Receiver Operating Curve: Unlike the confusion matrix: An ROC or receiver operator curve presents a visual illustration of the diagnostic ability of a model for binary classification. It involves plotting a graph between True Positive Rate (TPR) also known as sensitivity and False positive Rate also known as specificity at different threshold levels. Here, sensitivity and specificity are defined as

Sensitivity or TPR - The proportion of cases with actual positive result, Sn = TP/TP+FN, in other words, it tells how well the fake news was identified.

Specificity or FPR – The proportion of cases with actual negative results, Sp = TN/TN+FP, in other words, it tells how well the real news was identified by the model.

A ROC curve plots sensitivity and specificity at various classification threshold. If this threshold is lowered, both true positives and true negatives increase as shown in Figure 5. We would have run the model many times to find out the desired classification threshold. However, there is a better way to do that. The area under curve (AUC) is an effective method that can provide this information.

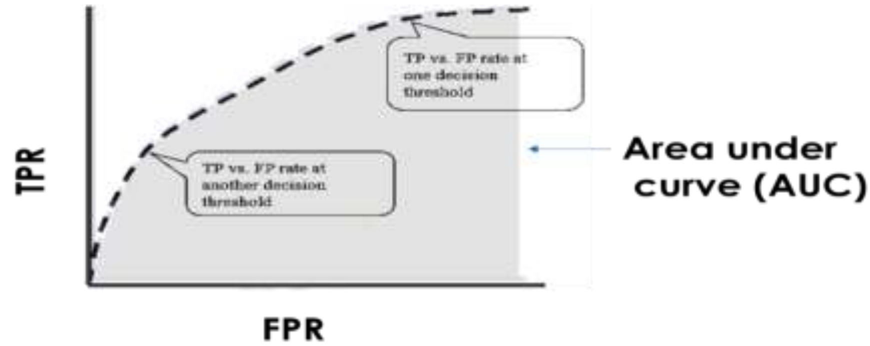

Figure 5: An ROC curve showing effect of lowering the classification threshold and Area under Curve

AUC score tells the efficiency of a classifier to differentiate the positive and negative classes (Fake and Real news) and its value varies from 0 to 1. The bigger the AUC, the better the given model in classifying the two classes. It is given by the formula

$$AUC = \int_0^1 f(x)dx$$

In other words, the closer the curve is to the upper left corner, the better its accuracy. The upper left corner means that the sensitivity is equal to 1 whereas the specificity is 0.

Results and Discussion

After preprocessing the data into TF-IDF vectors, we trained a Support Vector Machine (SVM) Classifier using 80% of the dataset to classify news articles as either Fake or True. The remaining 20% of the data was reserved for evaluating the model's performance. The evaluation metrics included a Confusion Matrix, Classification Report, and ROC curve analysis. Figure 6 displays the Confusion Matrix and Classification Report generated by the SVM Classifier.

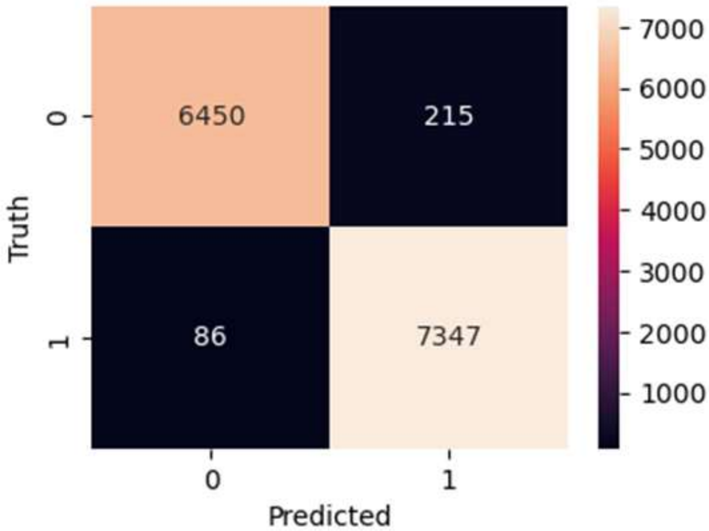

Figure 6: Confusion Matrix and Classification Report of Support Vector Machine Classifier

The Confusion Matrix illustrates that the model accurately classified 6450 articles as Fake news and misclassified 215 True news articles as Fake. Similarly, it correctly identified 7347 articles as True news while incorrectly classifying 86 Fake news articles as True. The overall accuracy achieved by the model is 97.86%. Precision scores indicate that Fake news was predicted with 98.68% precision and True news with 9716% precision. Recall scores show 96.77% for Fake news and 98.84% for True news (Table 2).

Table 2: The evaluation metrics results from the performance of the present model

	Precision	recall	f1-score	support
0	0.9868	0.9677	0.9772	6665
1	0.9716	0.9884	0.9799	7433
Accuracy			0.9786	14098
macro avg	0.9792	0.9781	0.9786	14098
weighted avg	0.9788	0.9786	0.9786	14098

Figure 7 depicts the ROC curve, showing an AUC value of 1.00, indicating excellent discriminatory performance of the model between Fake and True news.

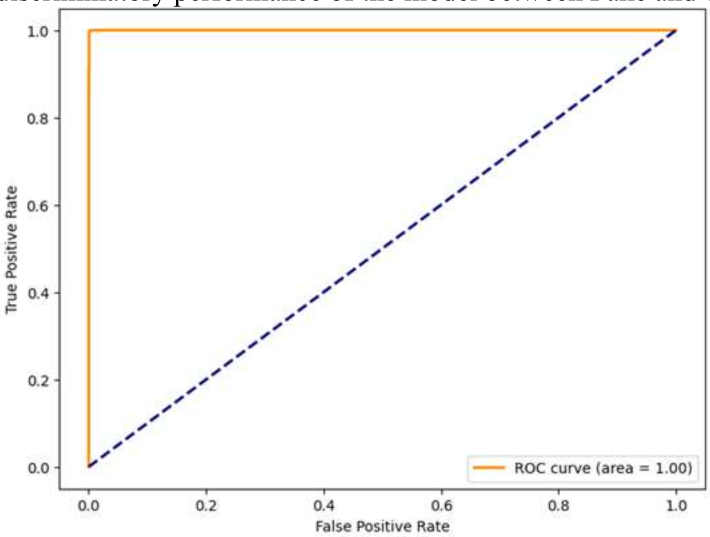

Figure 7: Support Vector Machine ROC Curve

Conclusion

The primary objective of this study was to discern patterns in text that distinguish fake articles from genuine news. Various textual features were extracted from the articles and utilized as inputs for the machine learning models. These models were trained and fine-tuned to optimize accuracy, with some demonstrating notably higher accuracy than others. Multiple performance metrics were employed to compare algorithmic results, revealing that ensemble learners consistently outperformed individual models across all metrics. The SVM classifier, trained on TF-IDF vectors to distinguish between Fake and True news, exhibited exceptional performance with an accuracy of 97.86%. The minimal misclassifications observed in the confusion matrix and the AUC value of 1.00 in the ROC curve further validate the model's robustness in accurately categorizing news articles. These findings affirm the SVM model's effectiveness in combating misinformation by reliably identifying and classifying news content.

Detecting fake news poses several unresolved challenges warranting further investigation. One critical area involves identifying key factors influencing the dissemination of fake news to curb its proliferation. Techniques rooted in graph theory and machine learning could prove instrumental in pinpointing pivotal sources involved in the spread of misinformation.

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