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# MACHINE LEARNING CLASSIFICATION BASED FAKE NEWS DETECTION

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**ABSRACT**: **In our modern era where the internet is ubiquitous, everyone relies on various online resources for news. Along with the increase in the use of social media platforms like Facebook, Twitter, etc. news spread rapidly among millions of users within a very short span of time. The spread of fake news has far-reaching consequences like the creation of biased opinions to swaying election outcomes for the benefit of certain candidates. Moreover, spammers use appealing news headlines to generate revenue using advertisements via click-baits. The rapid adoption of social media platforms (such as Facebook and Twitter) paved the way for information dissemination that has never been witnessed in the human history before. With the current usage of social media platforms, consumers are creating and sharing more information than ever before, some of which are misleading with no relevance to reality. In this analysis, they described a system for Fake news detection that uses machine learning techniques. They also described a dataset of fake and true news to train the described system. Obtained results show the efficiency of the system.**

**KEYWORDS: Fake news, Social media, Web Mining, Machine Learning**

## I. INTRODUCTION

In the last decade, Fake News phenomenon has experienced a very significant spread, favored by social networks. This fake news can be broadcasted for different purposes. Some are made only to increase the number of clicks and visitors on a site. Others, to influence public opinion on political decisions or on financial markets.

For example, by impacting the reputation of companies and institutions on the Web.
Fake news concerning health on social media represents a risk to global health. The WHO warned in February 2020 that the COVID-19 outbreak had been accompanied by a massive 'infodemic', or an overabundance of information—some of which was accurate and some of which was not—which made it difficult for people to find reliable sources and trustworthy information when they needed it. The consequences of disinformation overload are the spread of uncertainty, fear, anxiety and racism on a scale not seen in previous epidemics [1].

The advent of the World Wide Web and the rapid adoption of social media platforms (such as Facebook and Twitter) paved the way for information dissemination that has never been witnessed in the human history before. Besides other use cases, news outlets benefitted from the widespread use of social media platforms by providing updated news in near real time to its subscribers. The news media evolved from newspapers, tabloids, and magazines to a digital form such as online news platforms, blogs, social media feeds, and other digital media formats [20]. It became easier for consumers to acquire the latest news at their fingertips. Facebook referrals account for 70% of traffic to news websites. These social media platforms in their current state are extremely powerful and useful for their ability to allow users to discuss and share ideas and debate over issues such as democracy, education, and health. However, such platforms are also used with a negative perspective by certain entities

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commonly for monetary gain [3] and in other cases for creating biased opinions, manipulating mindsets, and spreading satire or absurdity. The phenomenon is commonly known as fake news.

There has been a rapid increase in the spread of fake news in the last decade, most prominently observed in the 2016 US elections. Such proliferation of sharing articles online that do not conform to facts has led to many problems not just limited to politics but covering various other domains such as sports, health, and also science [2]. One such area affected by fake news is the financial markets, where a rumor can have disastrous consequences and may bring the market to a halt. Our ability to take a decision relies mostly on the type of information we consume; our world view is shaped on the basis of information that digest. There is increasing evidence that consumers have reacted absurdly to news that later proved to be fake. One recent case is the spread of novel corona virus, where fake reports spread over the Internet about the origin, nature, and behavior of the virus. The situation worsened as more people read about the fake contents online. Identifying such news online is a daunting task.

Fortunately, there are a number of computational techniques that can be used to mark certain articles as fake on the basis of their textual content [16]. Majority of these techniques use fact checking websites such as “PolitiFact” and “Snopes.” There are a number of repositories maintained by researchers that contain lists of websites that are identified as ambiguous and fake. However, the problem with these resources is that human expertise is required to identify articles/websites as fake. More importantly, the fact checking websites contain articles from particular domains such as politics and are not generalized to identify fake news articles from multiple domains such as entertainment, sports, and technology.

The World Wide Web contains data in diverse formats such as documents, videos, and audios. News published online in an unstructured format (such as news, articles, videos, and audios) is relatively difficult to detect and classify as this strictly requires human expertise. However, computational techniques such as Natural Language Processing (NLP) can be used to detect anomalies that separate a text article that is deceptive in nature from articles that are based on facts. Other techniques involve the analysis of propagation of fake news in contrast with real news. More specifically, the approach analyzes how a fake news article propagates differently on a network relative to a true article. The response that an article gets can be differentiated at a theoretical level to classify the article as real or fake. A more hybrid approach can also be used to analyze the social response of an article along with exploring the textual features to examine whether an article is deceptive in nature or not.

It is, thus, imperative to recognize tricky conduct precisely so as to upkeep the lawfulness. Internet-based life can be described as a virtual existence where individuals collaborate with one another without the human feel and contact. It is anything but difficult to not uncover one’s character as well as profess to be another person on the internet based life. Cyberbullying is progressively turning into a typical issue among adolescents these days. These incorporate spreading gossipy tidbits about an individual, dangers, and inappropriate behavior. Cyberbullying unfavorably influences the person in question and prompts an assortment of passionate reactions, for example, brought down confidence, expanded self-destructive considerations, outrage, and wretchedness. Youngsters fall prey to these assaults because of their failure to grasp the sophistry and self-absorbed conduct of the aggressor. Another territory where a misleading location is of central significance is with the expanded number of false stories or fake News, on the Internet. Late reports recommend that the result

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of the U.S. Presidential Elections is because of the ascent of online phony news [4]. Advocates use contentions that, while now and again persuading, are not really legitimate. Web-based life, for example, Facebook and Twitter, have turned into the propellers for this political purposeful publicity. Nations around the globe, for example, France, are utilizing strategies that would keep the spread of phony news amid their decisions. Despite the fact that these measures may help, there is a squeezing requirement for the computational phonetics network to devise productive strategies to battle Fake News given that people are poor at distinguishing double-dealing. Hence, it is in extraordinary need of a programmed indicator to relieve the genuine negative effects brought about by the fake news. There are many methodology such as correlation filter based tracking algorithms non-negative least square algorithm, Online Representative Sample Selection method, regularization framework, multiple feature fused model have been introduced.

## II. LITERATURE SURVEY

M. Granik and V. Mesyura et. al. [9] shows a simple approach for fake news detection using naive Bayes classifier. This approach was implemented as a software system and tested against a data set of Facebook news posts. They were collected from three large Facebook pages each from the right and from the left, as well as three large mainstream political news pages (Politico, CNN, ABC News). They achieved classification accuracy of approximately 74%. Classification accuracy for fake news is slightly worse. This may be caused by the skewness of the dataset: only 4.9% of it is fake news.

H. Gupta, M. S. Jamal, S. Madisetty and M. S. Desarkar et. al. [5] described a framework based on different machine learning approach that deals with various problems including accuracy shortage, time lag (BotMaker) and high processing time to handle thousands of tweets in 1 sec. Firstly, they have collected 400,000 tweets from HSpam14 dataset. Then they further characterize the 150,000 spam tweets and 250,000 non- spam tweets. They also derived some lightweight features along with the Top-30 words that are providing highest information gain from Bag-of-Words model. 4. They were able to achieve an accuracy of 91.65% and surpassed the existing solution by approximately18%.

M. L. Della Vedova, E. Tacchini, S. Moret, G. Ballarin, M. DiPierro and L. de Alfaro et. al. [6] first proposed a novel ML fake news detection method which, by combining news content and social context features, outperforms existing methods in the literature, increasing its accuracy up to 78.8%. Second, they implemented their method within a Facebook Messenger Chabot and validate it with a real-world application, obtaining a fake news detection accuracy of 81.7%. Their goal was to classify a news item as reliable or fake; they first described the datasets they used for their test, then presented the content-based approach they implemented and the method they proposed to combine it with a social-based approach available in the literature. The resulting dataset is composed of 15,500 posts, coming from 32 pages (14 conspiracy pages, 18 scientific pages), with more than 2, 300, 00 likes by 900,000+ users. 8,923 (57.6%) posts are hoaxes and 6,577 (42.4%) are non-hoaxes.

C. Buntain and J. Golbeck et. al. [10] develops a method for automating fake news detection on Twitter by learning to predict accuracy assessments in two credibility-focused Twitter datasets: CREDBANK, a crowd sourced dataset of accuracy assessments for events in Twitter, and PHEME, a dataset of potential rumors in Twitter and journalistic assessments of their accuracies. They apply this method to Twitter content sourced from BuzzFeed's fake

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news dataset. A feature analysis identifies features that are most predictive for crowd sourced and journalistic accuracy assessments, results of which are consistent with prior work. They rely on identifying highly retweeted threads of conversation and use the features of these threads to classify stories, limiting this work's applicability only to the set of popular tweets. Since the majority of tweets are rarely retweeted, this method therefore is only usable on a minority of Twitter conversation threads.

S. B. Parikh and P. K. Atrey et. al. [7] presented an insight of characterization of news story in the modern diaspora combined with the differential content types of news story and its impact on readers. Subsequently, we dive into existing fake news detection approaches that are heavily based on text-based analysis, and also describe popular fake news datasets. We conclude the paper by identifying 4 key open research challenges that can guide future research. It is a theoretical Approach which gives Illustrations of fake news detection by analyzing the psychological factors.

H. Ahmed, I. Traore, and S. Saad et al. [11] described an extracting linguistic features such as n-grams from textual articles and training multiple ML models including K-nearest neighbor (KNN), support vector machine (SVM), logistic regression (LR), linear support vector machine (LSVM), decision tree (DT), and stochastic gradient descent (SGD), achieving the highest accuracy (92%) with SVM and logistic regression. According to the research, as the number of *n* increased in *n*-grams calculated for a particular article, the overall accuracy decreased. The phenomenon has been observed for learning models that are used for classification.

K. Shu, A. Sliva, S. Wang, J. Tang, and H. Liu et al. [12] achieved better accuracies with different models by combining textual features with auxiliary information such as user social engagements on social media. The authors also discussed the social and psychological theories and how they can be used to detect false information online. Further, the authors discussed different data mining algorithms for model constructions and techniques shared for features extraction. These models are based on knowledge such as writing style, and social context such as stance and propagation.

W. Y. Wang, *Liar* et.al [13] used textual features and metadata for training various ML models. The author focused mainly on using Convolutional Neural Network (CNN). A convolutional layer is used to capture the dependency between the metadata vectors, followed by a bidirectional LSTM layer. The maxpooled text representations were concatenated with the metadata representation from the bidirectional LSTM, which was fed to fully connected layer with a softmax activation function to generate the final prediction. The research is conducted on a dataset from political domain which contains statements from two different parties. Along with that, some metadata such as subject, speaker, job, state, party, context, and history are also included as a feature set. Accuracy of 27.7% was achieved with combination of features such as text and speaker, whereas 27.4% accuracy was achieved by combining all the different metadata elements with text.

B. Riedel, I. Augenstein, G. P. Spithourakis, and S. Riedel et al. [14], described stance detection system that assigns one of four labels to an article, "agree," "disagree," "discuss," or "unrelated," depending on the conformity of article headline with article text. The authors used linguistic properties of text such as Term Frequency (TF) and Term Frequency-Inverse Document Frequency (TF-IDF) as a feature set, and a Multilayer Perceptron (MLP) classifier is used with one hidden layer and a softmax function on the output of the final layer. The

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dataset contained articles with a headline, body, and label. The system's accuracy on the "disagree" label on test examples was poor, whereas it performs best with respect to the "agree" label. The authors used a simple MLP with some fine-tuned hyperparameters to achieve an overall accuracy of 88.46%.

S. Vosoughi, D. Roy, and S. Aral et al. [8] explored the properties of news spread on social media; i.e., the spread of news (rumors) on social media such as Twitter and analyzed how the spread of fake news differs from real news in terms of its diffusion on Twitter. Multiple analysis techniques are discussed to explore the spread of fake news online, such as the depth, the size, the maximum breadth, the structural virality, the mean breadth of true and false rumor cascades at various depths, the number of unique Twitter users reached at any depth, and the number of minutes it takes for true and false rumor cascades to reach depth and number of Twitter users.

Ruchansky N, Seo S, Liu Y et al. [15] utilize social commitment at the post level to catch the distinctions in transient commitment designs among phony and genuine news. Since individuals express their feelings towards news through web-based social networking post thus it is sensible to utilize web-based life posts as a potential component for highlight location.

## III. FRAME WORK OF MACHINE LEARNING CLASSIFICATION BASED FAKE NEWS DETECTION

Dataset is collected from fact-checking website PolitiFact through its API. It includes 12,836 human labelled short statements, which are sampled from various contexts, such as news releases, TV or radio interviews, campaign speeches, etc. The labels for news truthfulness are fine-grained multiple classes: pants-fire, false, barely-true, half-true, mostly true, and true. The data source used for this project is LIAR dataset which contains 3 files with .csv format for test, train and validation.

Online news can be collected from different sources, such as news agency homepages, search engines, and social media websites. However, manually determining the veracity of news is a challenging task, usually requiring annotators with domain expertise who performs careful analysis of claims and additional evidence, context, and reports from authoritative sources. Generally, news data with annotations can be gathered in the following ways: Expert journalists, Fact-checking websites, Industry detectors, and Crowd sourced workers. However, there are no agreed upon benchmark datasets for the fake news detection problem.

Data cleaning/ exploration means data while reading data, we get data in the structured or unstructured format. A structured format has a well-defined pattern whereas unstructured data has no proper structure. In between the 2 structures, we have a semi-structured format which is a comparably better structured than unstructured format. Cleaning up the text data is necessary to highlight attributes that we're going to want our machine learning system to pick up on. Cleaning (or pre-processing) the data typically consists of a number of steps:

a) Remove punctuation

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Punctuation can provide grammatical context to a sentence which supports our understanding. But for our vectorizer which counts the number of words and not the context, it does not add value, so we remove all special characters. eg: How are you? >How are you

b) Tokenization

Tokenizing separates text into units such as sentences or words. It gives structure to previously unstructured text. eg: Plata o Plomo-> 'Plata','o','Plomo'.

c) Remove stopwords

Stopwords are common words that will likely appear in any text. They don't tell us much about our data so we remove them. eg: silver or lead is fine for me-> silver, lead, fine.

d) Stemming

Stemming helps reduce a word to its stem form. It often makes sense to treat related words in the same way. It removes suffices, like "ing", "ly", "s", etc. by a simple rule-based approach. It reduces the corpus of words but often the actual words get neglected. eg: Entitling, Entitled -> Entitle. Note: Some search engines treat words with the same stem as synonyms.

The preprocessed dataset is divided into two parts: the first for training and the second for testing. The training module uses the training dataset and support vector machine algorithm to build a decision model that can be applied to the test dataset. If the model is accepted (i.e., it is able to achieve an acceptable accuracy rate), it can be kept and used and then training ends. Otherwise, the parameters of the learning algorithm are revised in order to improve the accuracy rate.

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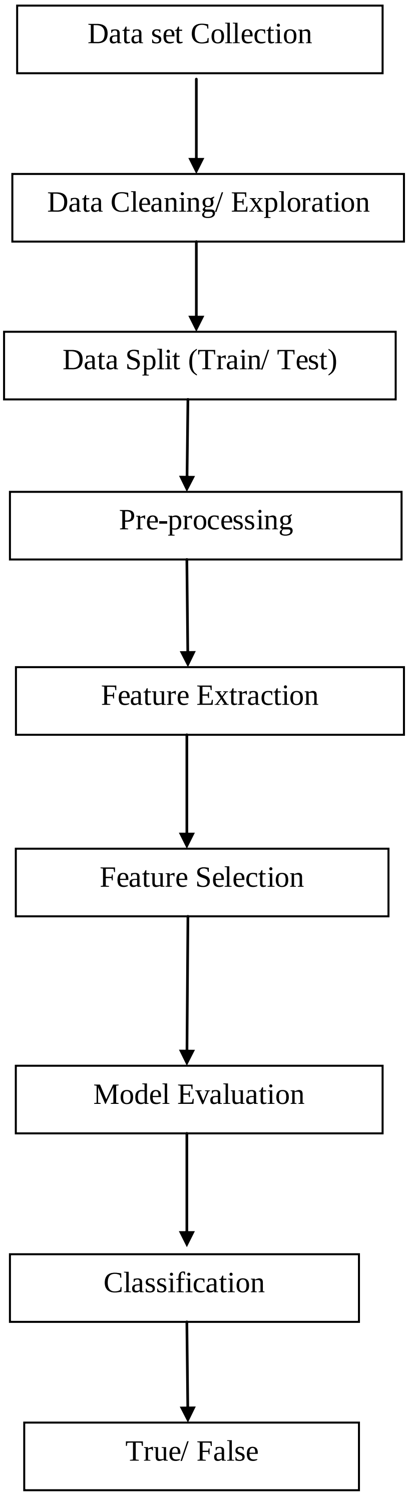


**Fig.1**: **Frame Work Of Machine Learning Classification Based Fake News Detection**

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This allows using the value of the decision function given for a news as a confidence level of its classification: a positive value for the decision function designates, at the same time, a true news as well as its degree of truth and vice-versa, a negative value of the decision function designates a Fake news as well as its degree of fakeness.

In the news dataset, news characteristics are classified into three categories: textual data, categorical data and numerical data. Each category preprocessing is performed through a set of operations. Text data requires preprocessing before applying classifier on it, so we will clean noise, using Stanford NLP (Natural language processing) for POS (Part of Speech) processing and tokenization of words, then we must encode the resulted data as integers and floating point values to be accepted as an input to ML algorithms.

Feature extraction is a process of dimensionality reduction by which an initial set of raw data is reduced to more manageable groups for processing. A characteristic of these large data sets is a large number of variables that require a lot of computing resources to process. Feature extraction is the name for methods that select and /or combine variables into features, effectively reducing the amount of data that must be processed, while still accurately and completely describing the original data set.

Then, feature selection methods are applied to experiment and choose the best fit features to obtain the highest precision, according to confusion matrix results. We propose to create the model using different classification algorithms. The product model will test the unseen data, the results will be plotted, and accordingly, the product will be a model that detects and classifies fake articles and can be used and integrated with any system for future use.

Model evaluation is the process of using different evaluation metrics to understand a machine learning model's performance, as well as its strengths and weaknesses. Model evaluation is important to assess the efficacy of a model during initial research phases, and it also plays a role in model monitoring.

The main goal is to apply a set of classification algorithms to obtain a classification model in order to be used as a scanner for a fake news by details of news detection and embed the model in python application to be used as a discovery for the fake news data. Also, appropriate refactorings have been performed. After the classification the statement have to check whether true or false.

## IV. RESULT ANALYSIS

In this section fake news detection using machine learning is observed. The highest accuracy is achieved by described classification method in comparison with existing methods. This result clearly proves that all the features selected and ML techniques used, prove effective in accurately detecting the fake news when compared compared with known existing models. In this system Navie Bayes, support vector machine and CNN classifiers are used.

The performance is evaluated based on the classified instances namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) which are defined as follows:

True Positive: If news is predicted correctly as positive and actually it is positive.

True Negative: If news is correctly predicted as negative and actually it is negative.

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False positive: If news is incorrectly predicted as negative but actually it is positive.

False Negative: If news is predicted incorrectly as positive but actually it is positive.

Based on these values the performance metrics like precision, accuracy, specificity and F1 score are measured for performance evaluation of presented system.

Accuracy: It is a performance parameter that measures the ability of the system to make correct predictions and expressed as

Accuracy= $\frac{TP+TN}{TP+FP+TN+FN}$ x 100 --- (1)

Precision: Precision measures the capability of a system to produce only relevant results.

Precision= $\frac{TP}{(TP+FP)}$ x 100 ---- (2)

Sensitivity: It is also known as True Positive Rate (TPR) or Recall. It is a performance parameter that measures the ability of the system to make correct positive predictions.

Sensitivity= $\frac{TP}{TP+FN}$ x 100

**Table 1: Performance Comparison Table**

| ML classifiers | NB | SVM | CNN |
|---|---|---|---|
| Efficiency | 99 | 88 | 91 |
| Accuracy | 98.9 | 85.7 | 90.3 |
| Sensitivity | 91.7 | 83.9 | 79.8 |
| Precision | 89.6 | 78.4 | 71.4 |

In fig.2 accuracy comparision graph is observed inbetween SVM, NB and CNN for fake news detecting using machine learning.

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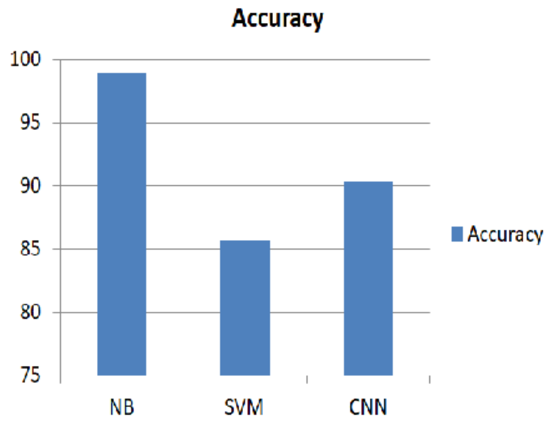


**Fig.2: Accuracy Comparison Graph**

For NB, SVM and CNN an comparison graph is drawn. And NB shows higher efficiency compared with SVM and CNN in fig.3.

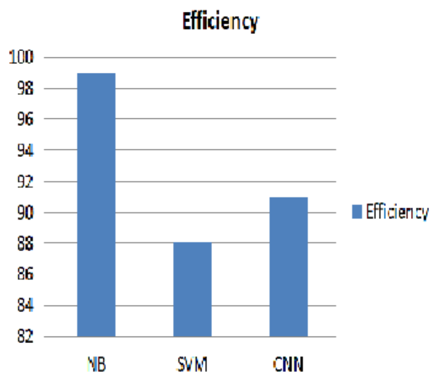


**Fig.3: Efficiency Comparison Graph**

Comparision graph of sensitivity for fake news detection using ML for NB, SVM and CNN is observed in fig.4.

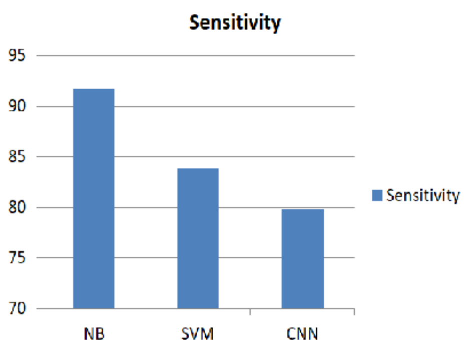


**Fig.4: Sensitivity Comparison Graph**

In fig.5 fake news detection graph is observed for precision of NB, SVM and CNN.

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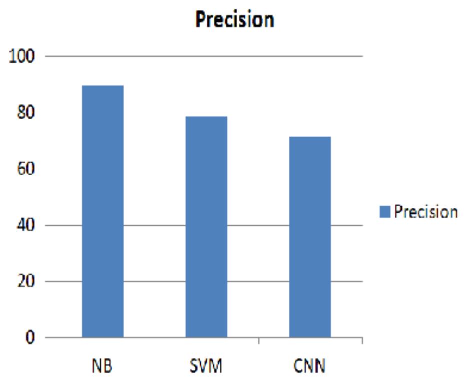


**Fig.5: Precision Comparison Graph**

Therefore described model for fake news detection has better results compared to SVM and CNN classifiers in terms of accuracy, efficiency, sensitivity and precision.

## V. CONCLUSION

In the 21st century, the majority of the tasks are done online. Newspapers that were earlier preferred as hard-copies are now being substituted by applications like Facebook, Twitter, and news articles to be read online. Whatsapp's forwards are also a major source. The growing problem of fake news only makes things more complicated and tries to change or hamper the opinion and attitude of people towards use of digital technology. When a person is deceived by the real news two possible things happen- People start believing that their perceptions about a particular topic are true as assumed. Thus, in order to curb the phenomenon, we have developed our Fake news Detection system that takes input from the user and classify it to be true or fake. To implement this, various NLP and Machine Learning Techniques have to be used. The model is trained using an appropriate dataset and performance evaluation is also done using various performance measures. The best model, i.e. the model with highest accuracy is used to classify the news headlines or articles. Hence the model achieved best results interms of accuracy, efficiency, sensitivity and precision.

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