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A Comparison of Machine Learning Algorithms in Fake News Detection

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ABSTRACT: Fake news has turned out to be a menace. Distinguishing Fake news is a critical advance towards safeguarding the uprightness and prosperity of the society. With the increasing popularity of social media, there's an upsurge in the propagation of counterfeiting news. There is a lack of proper frameworks for dealing with fake news. The proposed work aims at exploring the various machine learning techniques for detection and analysis of fake news. In this way, the accompanying task goes for proposing a worldview for ordering counterfeit news and utilizing learning systems such as Naïve Bayes, Support Vector Machines, Stochastic Gradient Descent and Neural Networks and draws an act comparison between the same. The analysis is based on a dataset of 20000 news samples collected from various sources including social media, news websites, online gossips etc. pre-processed using TF-IDF and count vectorizer. Similar ideas are utilized for incorporating an assessment investigation application for a sample 2014 American Presidential Election social media dataset which depicts user behavior with relevant subjects dependent on pertinence, freshness and criticalness. The model results in an underlying accuracy of 93% with further improvements to be expected based on cross-referencing, dynamism and tracking history of reputation of news sources. The research in the area of fake news detection has been vastly inhibited by lack of quantity and quality of existing datasets along with algorithms to model the given problems. To counter this issue, we thoroughly assemble and outline trademark machine learning algorithms and a context-independent dataset for analysis.

Keywords: Fake News, Machine Learning, Naïve Bayes Neural Networks, Support Vector Machines.

I. INTRODUCTION

The vast increment of social networking users previously scarce, over the years has prompted a mind-boggling amount of data being accessible every minute. The simple openness and accessibility of these platforms permits the utilization of data at a separation of a click on the mouse. In this manner, customary and autonomous news agencies have embraced web-based social networking extend to a more extensive group of audience thus increasing their customer base. The simplicity of making and dispersing content in informal communities like Twitter and Facebook has added to the rise of pernicious clients. Specifically, clients that corrupt the system with the spread of fake news. Before dealing with fake news, the most important challenge is to define how we can describe real and fake news. With the 2016 US Elections, the topic of fake news has been in discussion. There exists a lack of proper framework which can be adopted in order to deal with the increasing amount of fake news. There even exist a bunch of sites that produce fraudulent news only. They purposely distribute lies, publicity and disinformation implying to be genuine news – regularly utilizing social media to drive web traffic and intensify their impact. The fundamental objective of fake news sites is to influence the popular conclusion on specific issues (generally political). Numerous researchers trust that fake news issue might be tended to by methods for AI and machine learning. With tremendous research in the field of artificial intelligence, the algorithms to solve classification problems have started performing better than ever before. A fake news identification system intends to distinguish and explore assortments of possibly misleading news. The forecast of the odds that a specific news content is deliberately deceptive depends on the investigation of previously observed real and fraudulent news samples. A shortage of news samples, accessible as corpora for training the model, is a noteworthy hindrance in this field of algorithmic approach and solving this natural language processing problem [1-3]. The different pre-existing fake news models were context-specific in nature. There exists a lack of proper framework for categorization of types of deceptions that can occur in dealing with textual data. This paper examines a series of methods and types of deception that can be encountered when dealing with online news content and gauges their advantages and disadvantages for predictive modelling. It provides an algorithmic approach for solving the given problem. The paper explores the following components of fake news, in order to establish a distinction among the various models available:

(a) Defining fake news with respect to content, properties and types.
(b) Identifying sources of fake news.

(c) Analysing the various available corpora (datasets) for fake news detection.

(d) Building a data model for identifying the relevant news information

(e) Fetching the data, establishing metrics for evaluation of fake news.

(f) Classification, handling, processing and using the data to perform predictions.

II. LITERATURE SURVEY

A. Previously used Techniques

Social media, a popular source of news and information following Newspapers and Televisions can also serve as a source of false news and misleading information. According to latest reports, there are 1.2 Billion users of the most popular social media website: Facebook. So, websites like these are clearly one of the ways in which fake news can be circulated extensively to a large number of people. Hence, it is very difficult to detect fake news on social media platforms. One approach is to account psychological and social theories for evaluation from a data mining perspective. The reasons why people prefer to read news on these sites can vary. Less time consuming, easy to share and comment on the issue of article, discussion on the topic, etc. can be few of them. There are few steps that are necessary to take in the process from Characterization to Detection of these kinds of news. They have a particular style in which they are written and based on Knowledge of the systems; these can be detected and produced to the consumer as fake or real [4]. There are many malicious accounts on the internet which spread such information. These are the news which one can easily spot on internet as they are spammed everywhere possible by spreaders. Other ways include Click-Bait detection, Rumour Classification, Spammer Detection, Bot Detection, etc [5].

The major challenge in the detection of fake news is the availability of appropriate data to perform analysis. Most of the datasets available are either vague or lack proper structuring. However, with continual research, there has been a growth in corpora for identifying fake news [6, 7]. A study by BuzzFeed in late 2016 collected more than 2000 posts from top and verified pages on Facebook. Each of the post was checked by BuzzFeed journalists on factual data available. These posts were labelled as 'Mostly True' or 'Mostly False' by them. After this, posts were analysed on based on the engagements. It was done with the help of number of shares, comments and likes/reactions. In order to train the models, datasets from CREDBANK and PHEME were used. Formalization of four processes was done: Featuring accuracy prediction, aligning datasets, selection of features and to evaluate models based on metrics. Accuracy of 65.29% was observed which is acceptable at the level at which over fitting is avoided [8].

Another notifying survey was done after the course of 45th President Election of United States. It was felt necessary to take control over fake news online to ensure that none of the supporters could spread fake news about the competing representatives. With the help of Logistic Regression, Support Vector Machines, long short-term memory networks and a convolution neural network model, various learning-based methods were evaluated. Text and meta-data were integrated with new neural network architecture. LIAR, a dataset which set benchmark in the support of fake news detection was formulated with the help of these techniques which made detection and fact-checking easy. The dataset not only included statements from social media or internet, but also those were said on television by the famous personalities and were later criticized by the critics and journalists. The problem is framed as 6-way multi-class text classification. Based on a randomly initialized matrix of vectors, in which metadata embeddings are done and standard max-pooling operation that was performed on it which is then fed to a SoftMax activation function, a final prediction is generated [9].

Even on taking various detection methods into account, enough ways still can be derived to find one through which or another, fake news still can be circulated on internet. The classification on the basis of Content (What), Social (Who) and Temporal (When) is very crucial in the decision making and prediction for any kind of model that have been designed so far. This forms a 3-tiered information set. Apart from this, categorisation also depends on secondary factors like Network Properties and Type of Network. On analysing these attributes, all the models basically predict the news validity with a factor that measures the Truth Values. For example, these truth values can be based on the factors like reliability, historical review of accuracy of information provided by the source, number of persons who trust on the source for any kind of information, etc. Interaction network, which describes relationships among the different entities such as publishers, news pieces and user, is formed and based by the truth values. Size of the network for a particular news or article is defined as the number of users who potentially get affected by the news piece, which needs to be controlled in case of fake news detection. Network intervention aims at formulating strategies to control the spread of fake news before it goes viral [10].

Various methodologies have been applied for deception identification via social media. The detection of fake news can be isolated into two classifications, one depends on the language and the other dependent on the source of data. Most liars utilize their language deliberately with the intention to deceive. Despite the endeavour to control what they are stating, language "spillage" happens with certain verbal perspectives that are difficult to screen, for example, frequencies and examples of pronoun, combination, sentiment and word usage. The objective in the etymological methodology is to search for such occurrences of spillage or, supposed "prescient misleading prompts" found in the substance of a message [11-13]. The most straightforward technique for dealing with natural language processing problems while building a model is the "bag of words" approach, which views each word as a solitary, equally significant unit [14, 15]. Taken care of words approach, singular words or "n-grams" (multiword) frequencies are collected and investigated to uncover signs of misrepresentation. Further labelling of words into individual lexical signs for instance, grammatical forms or "shallow grammar" are methods for giving recurrence sets to uncover semantic prompts of misdirection as portrayed in the different bits of research in the past. So as to distinguish fake news, it is essential to examine the various features that compose the same. Note that the previously mentioned attributes of customary fake news are likewise relevant to social media. There is a high possibility of users on social media to be malignant, biased and conspirators. A lot of these are employed for the spread of deception and troll, thus compromising the integrity of the web. Therefore, there needs to be a fool proof approach to handling this issue [16, 17].

B. Some commonly occurring types of fake news

Before working on the problem of fake news, it is essential to define the same and observe the various categories that may constitute it. Fake news is a form of sensationalist reporting or purposeful publicity that comprises of intentional disinformation or hoax spread by means of customary print, communicative news media or online social media. The news is regularly resonated as deception in social media however at times discovers its way to the predominant press as well. Fake news is composed and spread with the intention to delude or harm an office, a substance, an individual or gain monetarily, politically by regularly utilizing sentimentalist or deceptive features with a constant attempt at expanding the user traffic. It can be categorized as follows:

(a) Satire/Parody: Humorous attempts to ridicule a particular topic or person by use of irony, and exaggeration

(b) Bias/Conspiracy: Unfair prejudice against a person or a group of persons. May lead to fake news as a propaganda for maligning an image.

(c) Misinterpreted/Sloppy Reporting: News components that are not fully verified and are shared to support/oppose an individual or an opinion.

(d) iJunk Science/Gossip: Dubious claims without backing of facts.

(e) Clickbait and spams: Main intention is to drag the user's attention with a misleading headline often leading to unsolicited results.

(f) Deliberate Misinformation: Misleading information, intentionally fabricated as a sensationalist propaganda.

Therefore, with the lack of proper regularization frameworks spreading fake news and misleading information has become increasingly easy on social media. That is why we need fake news detection mechanisms in order to regularize the web framework and prevent any form of misleading information from spreading.

Table 1: A survey on pre-existing techniques.

Source	Process Involved	Inference
Conroy *et al.*, (2015) [1]	Deals with the processes involved from defining fake news to its detection and feature recognition and the different types of fake news.	Categorized fake news into serious fabrications, hoaxes and humorous fakes.
Kadian and Bhattacherjee (2018) [5]	Accounts for ways of spreading malicious content on internet ranging from Click-Bait, Rumours, Spamming and Bot. Explores methods to counter the same.	Features to differentiate a click-bait from genuine content includes difference in number of characters between post title and the article keywords, ratio between text image and a post's title.
Wang (2017) [6] Shu *et al*., (2017) [7] Buntain and Golbeck (2017) [8]	There is lack of sufficient fake news datasets. These papers explore the different datasets and feature extraction principles that were used.	The LIAR dataset provides a benchmark for fake news detection. The pre-processing methods and tagging of content is relevant for proper analysis.
Parikh and Atrey (2018) [9]	Exploring various available datasets and relevance of the benchmark PHEME and LIAR dataset with relevance to social media and internet data. Includes formulation of 6-way multi class text classification. It uses a SoftMax activation function for final prediction.	Calls for requirement of a multi-modal datasets for fake news detection. Methods like clustering rely on the size of the dataset.
Shu *et al.*, (2019) [10]	Explores the fake news sources and established a 3-tiered information set for classification based on Contextual, Social and Temporal referencing. Also explores challenges in realisation of source reliability.	Trends in fake news characterization by using network analysis. Entities involved can use network propagation for mitigation of fake news.
Tschiatschek *et al*., (2018) [13]	Utilises crowd signals for detecting fake news by using Bayesian influence.	Robust approach to use flagging in social media for identifying fake news.
Davis and Proctor (2017) [14] Long *et al*., (2017) [17]	The pre-processing techniques like bag of words and n-gram approach can be used for labelling and probabilistic estimation of word occurrences.	These methods are involved in lexical disambiguation and are used examine the various features relevant to analysis.

III. PROPOSED WORK

The proposed work explores a number of machine learning techniques as well as pre-processing methods for fake news detection. Some famous classifiers explored include Naïve Bayes Classifier, Support Vector Machines, Stochastic Gradient Descent and Neural Network Classifier. The different phases involved in the processing of the text for classification is given in Fig. 1.

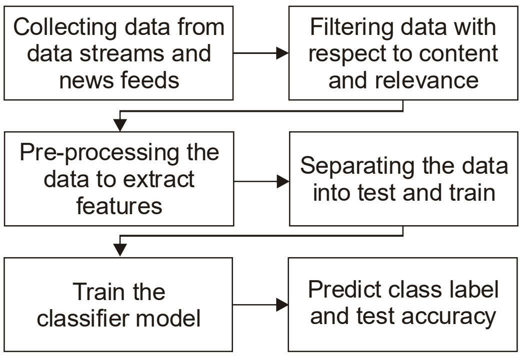

Fig. 1. The Process Flow.

The different classifiers used for analysing fake news are as follows:

(i) Naïve Bayes Classifier: Naïve Bayes is a simple probabilistic classifier which uses Bayes Theorem with strong independent assumptions among the features [18]. This can be stated as:

$$P(Y|X_1, X_{2,\ldots}X_n) = \frac{P(X_1|Y)P(X_2|Y)\ldots P(X_n|Y)}{P(X_1)P(X_2)\ldots P(X_n)}$$

which can be further expressed as:

$$P(Y|X_1, X_{2,\ldots}X_n) = \frac{P(Y)\prod_{i=1}^{n} P(X_i|Y)}{P(X_1)P(X_2)\ldots P(X_n)}$$

where P(X|Y) is the probability of an event X occurring, given Y has already occurred.

(ii) Support Vector Machines: A support vector machine is a discriminative classifier. It uses the concept of a hyperplane to separate the two classes. The algorithm aims to establish an optimal hyperplane, which in two dimensions is a line dividing a plane in two parts with the corresponding classes on either side of the hyperplane [19]. The boundary values in either classes are known as support vectors. Our aim is to maximise the distance of the hyperplane from the support vectors. Suppose, there exists a binary classifier with the given class label y and set of features x. Given y∈ [1, 1] where b is the bias and w refer to the weights of the vectors. The classifier can be written as follows:

$$h_{w,b}(x) = g(w^T x + b)$$

Here g(z)=1 if z>0 and g(z) = -1 otherwise

(iii) Stochastic Gradient Descent: An iterative, optimisation approach to the given problem. It involves selection of random/shuffled samples. It works by minimizing the loss of a given function.

The gradient descent procedure described above operates by updating the coefficients for each training instance, rather than at the end of the batch of instances [20].

$$Q(w) = \frac{1}{n}\sum_{i=1}^{n} Q_i(w)$$

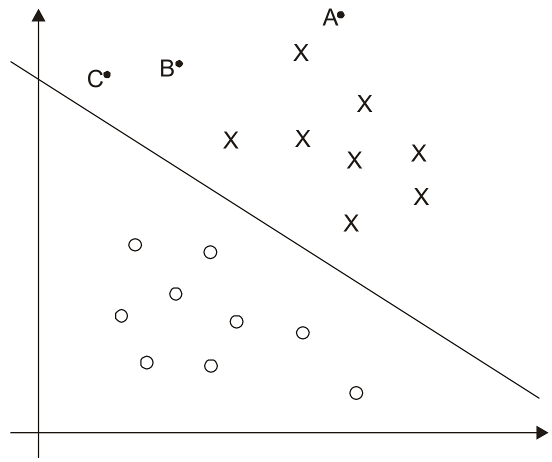

Fig. 2. SVM Hyperplane separating two classes and classifying points A, B and C.

IV. ALGORITHM

Step 1: Extract text from source.
Step-2: Preprocess the textual data.
– Sampling information.
– Remove Stop words.
– Normalize textual data to form vector matrix using tf-idf/count vectorizer.
– Generate feature matrix.
Step 3: Train-Test Split.
Step 4: Train the classifiers.
– Naïve Bayes.
– Support Vector Classifier.
– Stochastic Gradient Descent.
– Neural Networks.
Step 5: Test the algorithms.
Step 6: Evaluate performance of algorithm.

V. RESULTS AND ANALYSIS

After, we gathered the data. The different machine learning models were trained with their respective algorithms. Naïve Bayes, SVM, SGD and Neural Networks Classifiers were trained to solve the following natural language processing problem. The dataset consisted of the following features:

(i) Author/Source: The actor responsible for generating the given text. Can be either a user, news agency or an organisation.
(ii) Headline: The title or outline of the content.
(iii) Text: The body of the news in detail.
(iv) Class: The classification label either “Real” or “Fake”.

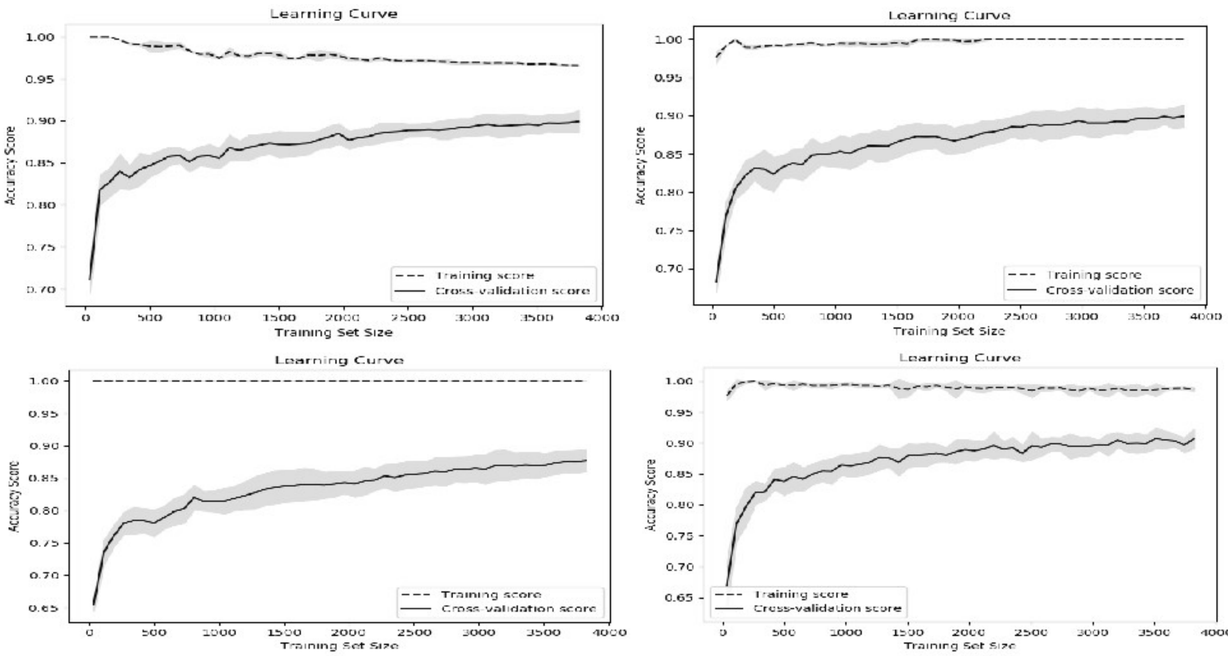

Fig. 3. The learning curve of Naïve Bayes, Support Vector Machine, Stochastic Gradient Descent and Neural Network Classifiers respectively for the given problem.

Table 2: Performance Evaluation of Algorithms.

Model	F-Score	Precision	Sensitivity	Specificity	Accuracy
Naïve Bayes	0.52	0.36	0.94	0.61	0.68
Support Vector Classifier	0.74	0.77	0.71	0.79	0.76
Gradient Descent	0.88	0.86	0.89	0.85	0.87
Neural Networks	0.93	0.94	0.92	0.93	0.92

Table 3: Comparative study of the performance of different algorithms.

Algorithm	Accuracy	Comment
Naïve Bayes	68.4%	Simple but high memory latency
Support Vector Machine	76.8%	Guaranteed Optimality but lose sequentiality
Stochastic Gradient Descent	87.5%	Faster learning rate but noisier
Neural Network	93.6%	Highly effective but computational requirement is quite high

The dataset was composed of textual data from sources like social media such as Twitter, Facebook, BuzzFeed and also various internet news sources. The Table 2 provides an in-depth performance evaluation of the algorithms and can be used to compute the final accuracy. All algorithms have certain merits and demerits which is specified in Table 3.

Algorithm tuning is a process of choosing a set of proper parameters for a learning algorithm. Hyper parameterization optimizes the parameters for finding an optimal value of alpha which minimizes the loss function.

Table 4: Alpha vs Score.

Alpha	Score
0	0.769
0.1	0.76364
0.2	0.72727
0.3	0.72121
0.4	0.70909
0.5	0.70909
0.6	0.69697
0.7	0.67879
0.8	0.67879
0.9	0.67819

Fig. 4. Parameter Tuning.

Fig. 4 performs a comparison between the parameter value of alpha and the score of the function. With increasing value of alpha, the error decreases. Table 4 compares the variation of the alpha value and the score for the classification problem.

After we train the machine learning models with proper parameters. We perform an analysis of the accuracy of the different functions. It is quite evident that the neural networks model for classification is highly efficient and yields an accuracy greater than the rest.

Fig. 5 compares the varying accuracy of the different machine learning models for the fake news detection problems.

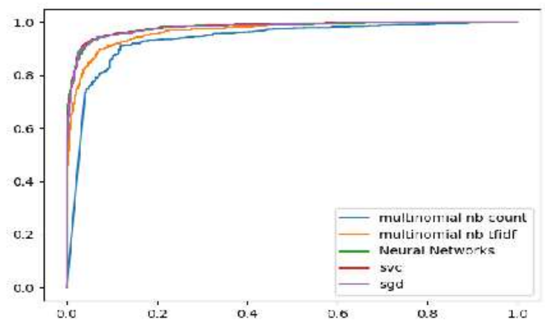

Fig. 5. Accuracy Comparison.

After establishing the performance evaluation of the different algorithms, one can explore the various datasets for finding out various features that make a given news fake or real. Applying the same classification models for a test set comprising of tweets from the United States Presidential Election yielded Fig. 6 and 7.

Fig. 6. Word Cloud for “Fake” News.

Fig. 7. Word Cloud for “Real” News.

VI. CONCLUSIONS

It can be seen that machine learning and artificial intelligence algorithms can be applied for detection of fake news. A number of different algorithms were implemented and their accuracies were observed. It was seen that although a neural networks model has high computational requirements it outperforms other models in terms of accuracy. The stochastic gradient classifier is the fastest learning algorithm. SVM uses the concept of hyperplanes instead of probability distributions, as seen in Naive Bayes, it is expected to perform better in the fake news detection. The accuracy scores of the different models have been given with a single decimal place and exhibit major differences in their performance as shown in Table 2 and 3. However, it must be noted that while working with different datasets containing millions of data points, the small percentage differences between the accuracy scores of the different models can make thousands of right predictions. Thus, it is imperative to note the figures up to one decimal place. The classification models were applied and the words were weighted in order to find the most informative feature for fake and real news with respect to the US General Election tweets. The word cloud for the same has been shown above. A number of tweets with the word “Russian and “Hilary” were marked fake with the highest weightage. The density of fake news had tremendously increased during that period as well. Therefore, it can be seen that the following algorithms offer an adept approach to solving the fake news menace. However, this doesn’t end as there are more rooms for improvement for the same.

VII. FUTURE SCOPE

The neural network approach provides an adequate method to model the problem of fake news detection. However, there lies a lot of scope for improvement. We assessed our models utilizing outright probability limits, which may not be the most dependable and lead to over fitting in certain cases. The current techniques do not provide a mechanism for contextual and cross referencing. Further improvements can be made to incorporate a dynamic method for news extraction and classification instead of using a static dataset for training. Tagging of sources and topics based on reputation could establish a more robust approach.

Conflict of Interest. There is no conflict of interest involving the content enlisted in the given paper.

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