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Fake News Detection Using Machine Learning Algorithms: A Review

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Abstract— The spread of false news in the digital age poses challenges to society. This paper studied machine learning techniques for detecting fake news, focusing on the best-performing algorithms and also commonly used datasets. Evaluation metric such as F1 score, accuracy, precision, recall, and performance are reviewed, along with the examination of datasets. Through the analysis and comparison of existing studies, algorithms demonstrating superior performance across evaluation metrics can be identified. Furthermore, widely employed datasets that yield reliable results are highlighted. This review enables researchers to make informed decisions in selecting accurate algorithms and effective datasets, advancing the field of fake news detection.

Keywords— Fake, Learning, Machine, News.

I. Introduction

The world is rapidly changing. Without a doubt, the digital world offers numerous benefits, however, it additionally has certain drawbacks. Today's technological age environment presents various challenges. Fake news is one of them. Someone can simply propagate false information. Fake news simply refers to false disseminated information in order to harm a person's or organization's reputation. It could be propaganda directed at a political party or an organization.

Detecting fake news requires machine learning algorithms that can learn from labeled datasets containing genuine and fake news articles. These algorithms can be trained to differentiate between the two categories based on various features and classifiers. Therefore, it is crucial to evaluate and compare the performance of different algorithms to identify the most effective approaches.

This study would discuss commonly employed evaluation metrics in the field of false news detection, such as performance, accuracy, precision, recall, as well as F1 score. Using these criteria, researchers may evaluate the efficiency of various machine learning techniques and select the most accurate and dependable models. Additionally, the review will explore the datasets used by researchers in this field.

To identify the best-performing algorithms, this study would rigorously examine and compare the findings of previous studies. The study, will consider the accuracy, precision, recall, and other evaluation metrics achieved by different algorithms on various datasets. By synthesizing these findings, the study would be possible to identify algorithms that consistently demonstrate superior performance across different evaluation metrics. Similarly, examining the datasets used by researchers will help identify widely employed datasets that have produced reliable results.

By combining insights gained from evaluating the performance of different algorithms and assessing dataset characteristics, researchers can make informed decisions about selecting algorithms and datasets for their own studies. The study would enable them to choose the best-performing algorithms and utilize the most suitable datasets, improving the reliability and accuracy of their fake news detecting models.

This present review studies aims to provide an overview of studies on fake news identification using machine learning techniques, with an emphasis on finding the best-performing algorithms and regularly used datasets. Researchers can make informed decisions about selecting accurate algorithms and useful datasets by evaluating algorithm performance and examining dataset features. And it contribution will help to advance the field of false news identification and encourage a spate development of dependable and effective solutions that will avoid the spread of false news in the digital era.

II. Literature Survey

The table I gives the summary of related research work carried out in this domain.

Table I. Review of Related Literature

Author	**Tittle**	**Methodology/Algorithms**	**Dataset**	**Results**
Z Khanam, BN Al wasel, H sirafoi ,M Rashid	Fake News Detection Using Machine Learming Approaches	R/ Forest, (KNN), Naiive Bayes, D/ Tree SVM XGboost	Main Liar Dataset is used as the Model.	Xboost outperformed Decision tree, Nave Bayes, and K-Nearest Neighbors with an accuracy of 75%
Celestine Iwendi a,b, Senthil kumar moohan c, suleiiman khaan D, ebukka Ibekee,Ali ahmadii , cianoo h	"covid-19 fake news sentiment analysis"	RNN, LSTM, as well as GRU	A dataset of 545 news articles collected from various from sources.	LSTM achieved the highest accuracy of 96.3%
Y.B Lasotte, E.J. garba, garba AB,Y.M. Malgwi, and M.A Buhari	An Ensemble Machine Learning Techniques for False news identification and Classification Using a soft Voting Classifier	Naïve Bayes, Support vector Machine(SVM). Logistic Regression, and Random forest.	**Kaggle fake news dataset.**	Logistic Regression achived the highest accuracy with 92%, SVM with 91%, Random Forest with 90%, Lastly Naïve Bayes with 88%.
Elminina am yomna, Mariam kkhaleed, Hasan, Raadwa Moutaafa , and Jhon Gergess, Diaa Salama, ABD	Fake news Detector Using Machine Learning techniques.	Support Vector Machine(sVm), D/ Tree, Neural Network	A politics dataset of 12,207 articles from kaggle.com Celebrity news dataset.	Hybrid Achieved the highest accuracy of 85.2%, followed by NNwith 84.7%, SVM 84.5% and Decision Tree with 81.1%
Qiheng G Gao and Nicole Lantz	Using Machine Learning Algorithm to Detect fake news	SVM, Multinomial NB, Boosting Trees, Latent Dirichlet Allocation+Gradient Boosting	Article dataset from Reuters.com	LDA+Gradient Boosting the highest accuracy 0f 100%, Multinomial NB has the worst result.
fathima Shanas and AF. Sharfana.	"Detection of False news on Twitter Regarding COVID-19: An Analysis of Machine Learning Algorithms with Ngram Modelling"	SVM, L/ Regression, D/ tree, R/forest, KNN classifier, Multinomial NB, Passive Aggressive, and Gradient Boost.	Covid-19FNIR Dataset from e IEEE Datas port websites.	SVM Produced outstanding results with an average accuracy of 99.13% and the highest accuracy of 99.3% on the Covid-19 FNIR Dataset
Asha. J, Meenako walshaly a. A	False News identification Using Unsupervised, D	Convolution neural network and recurrent Algorithms deep learning). One- Class SVM (Support Vector Machine)	News Dataset	CNN-RNN outperformed One-Class Accuracy of 96.4%
N.Leelaa Siva Ramaa, Krishnna, M. Adimoolam	"False News Identification System Using Logisitc regession and Compare Textual Property with Support Vector Machine"	LR Technique, the other group is the SVM support vector machine algorithm.	A dataset of10,000 news articles from various sources.	LR Achieved an accuracy of 94.02%while svm has 90.23%
Kai Shu,	"False	SVM	News and	Mediocre

Deepak Mahudes warman & Huan Lieu	newss Tracker A Tool for False News collection , Detection , Visualiza tion"	Support Vector Machine L/Regres sion Nave Bayes	social context data set	Accuracy 68.4%
Hader ahmed, Isa Traore & Sharif Sa'ad	"Online Detention of False Newss Using NGram Analysis &Machin e Learning "	N-Gram SVM KNN Logistic Regression	A Dataset of 10,000 news artcles	SVM achieved 92% accuracy uses bi

III. Methods and Techniques

Papers were gathered from several research databases. However, many of them were pertinent to the subject. As a result, the articles were initially rejected based on their titles as well as abstracts. An abstract is a concise summary of the full work that contextualizes the information provided. In the subsequent phase, the remaining papers were reviewed considering the inclusion and exclusion standards. Fifty-three (53) papers were retrieved from various search databases using search phrase. Ten studies remained after conducting the exclusion, which are discussed in this literature review. The search process is given in Fig. 1.

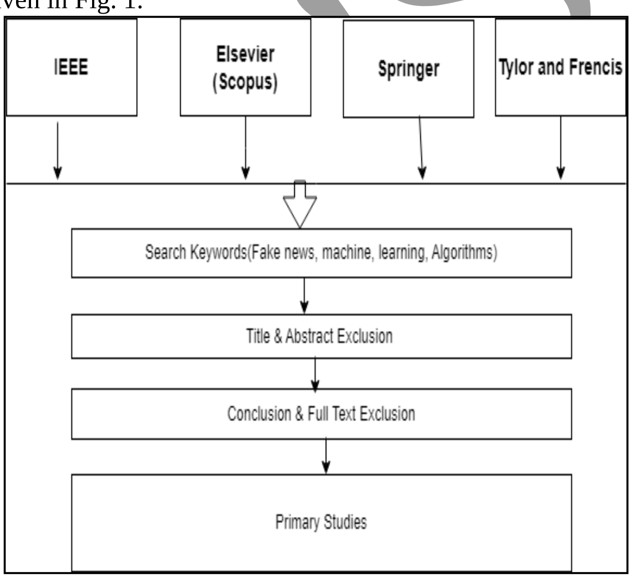

Fig. 1. Diagram of the Search Process

3.1 Decision Tree

Decision tree can be described as equipment which is having flow chart alike form that is initially used for problems related to classification. Every internal node of the decision tree provides a condition or "test" on an attribute, with branching based on the test conditions and results. Finally, the class label of the leaf node is determined after all attributes have been computed. The distance between the root and the leaf represents the classification rule. Incredibly, it can work with both categories and dependent variables. They are effective at finding the most critical elements and displaying their relationships. They play a crucial role in establishing new variables and characteristics useful for data exploration and accurately forecasting the target variable. (Z Khanam, et al. 2021).

$$P(c \mid x) = \frac{P(x \mid c)P(c)}{P(x)}$$

$$P(c \mid X) = P(x1 \mid c) \times P(x2 \mid c) \times \ldots \times P(x2 \mid c) \times P(c) \tag{1}$$

3.2 Random Forest

RF are based on the concept of creating many decision tree methods, each of which yields a distinct and novel result. The RF makes used predictions of a large number of dt to determine variance in the dt, the RF randomly chooses a sub-category of qualities from each cluster (Giselle Rampersad a, Pascale and Indrit 2010). Random forest is most helpful when used with uncorrelated decision trees. The overall result will be similar to that of a single decision tree when applied to similar trees. Uncorrelated decision trees can be generated using bootstrapping and feature randomness. (Naphaporn and Sukree 2011).

Bayesian naiveté This algorithm is grounded on Bayes theory and it is utilized in several machine learning problems. (Jasmin , Samed and Abdulhamit 2017). Basically, Naiive Bayes adopts that one function in a category has no bearing on another. For example, a vehicle is defined as a vehicle if it can move, has wheels, and has a diameter of more than 50 inches.
Whether above functions are practically dependent on one another or on distinct functions, Even if they are reliant on one another or on other functions, Naive Bayes assumes that each of these functions has its own proof of the vehicle. (Researchgate.net.2018).

3.3 Support Vector Machine

Can be described as a technique based on placing every piece of data as a point in a range of dimensions' n (the number of available characteristics), with the value of a particular property equal to the number of provided coordinate (Xun , et al. 2018). is based on placing every piece of data as a point in a range of dimensions' n (the number of available characteristics), with the value of a particular property equal to the number of provided coordinates.

3.4 KNN

KNN technique, the majority of the sound from the neighboring k with respect to them is used to classify new positions. Among the closest neighbours K, the class position is substantially mutually exclusive and is determined by the role of distance. (Researchgate.net).

3.5 Combining Classifiers

The primary drive of paradigm identifying systems is to get the top taxonomy performance feasible. As a result, many classification plans for action detection models can be advanced. Even if one model outperforms the others in terms of execution, the style sets correctly categorized by variant classifiers do not have to overlap. Planners for variant categorization may supply more data to the models. With this additional knowledge, each model execution can be enhanced. (ShivamB. et.al 2018).

CNN doesn’t produce adequate results on time series data because of the missing gradient problem. Hopfield proposed R.N.N in the year 1982 to address the aforementioned difficulty. RNN provides the advantage of informing the N.Ns about patterns over time. RNN predicts serial data behavior based on the earlier occurrences in video, voice recordings, text, items, and so on. Figure 3 depicts the RNN working system. (Celestine, et al. 2022).

3.6 LSTM

LSTM was developed as a remedy for short term memory. They have internal information-flow control systems known as gates. The said gates might understand data to keep or discard in a given arrangement. It would pass vital facts down the extended series chain in order to make estimation. Almost all state-of-the-art outcomes were obtained using these two networks and recurrent neural networks. (Celestine, et al. 2022).

3.7 GRU

GRU comprises three gates and it doesn’t maintain an Internal Cell state. The concealed state of the Gated Recurrent Unit incorporates the data stored in an LSTM recurrent unit in the Internal Cell State. (Celestine, et al. 2022). The collective data would be sent to the bellow Recurrent Gate Unit. GRU with various gate functionalities include the following:

Update Gates: This indicates the extent to which past data must be transferred to the next generation. It is analogous to the Input Gate of an LSTM recurrent cell. Reset gate: This specifies how much prior knowledge should be discarded. It is equal to combining the Input Gate and the Forget Gate in a recurrent LSTM unit.

3.8 Naiive Bayes

The conditional probability is calculated using Nave Bayes that can be defined as the possibility that something will happen given that something else has already happened. The presence of one feature in a class is independent of the presence of any other feature, according to the Naive Bayes classifier. Nave Bayes is easy to build, fast, and effective for large datasets. It is trustworthy for text classification problems since it can do binary or multiclass classifications. (Lasotte, et al. 2022).

LR is a form of supervised machine learning approach for classifying data. It uses a collection of independent variables to predict a categorical dependent variable. The logistic regression predictions are made in terms of the probability that an event will occur. Sigmoid function used in LR to change the output to a probability value; the goal is to minimize the cost function to achieve the best probability. Here is the sigmoid function:

$$sigmoidequation = \frac{1}{1 + e^{\wedge}(-x)} \tag{2}$$

Random forest is a versatile, straightforward, and diverse supervised machine learning technique. It can deal with Regression as well as classification issues. it creates collective of decision tree models aimed to enhance prediction outcomes. In classification, decision trees function independently to forecast the outcome of a class, with the class with the most votes being the final prediction. (Pal 2005).

A version of the SVM is one-class SVM. SVM is an unsupervised learning technique that learns a decision function for novelty detection and distinguishes between fake and authentic news. The one-class SVM finds a hyperplane that separates the news dataset from the dataset's origin and is as near to the data points as possible. The one- class SVM is a pre-installed package in SK-learn. (Kai, et al. 2017).

A Convolution neural network (CNN) where connections between nodes do not form a cycle) and employ a multilayer perceptron version designed to need little preprocessing. These are inspired by the visual cortex of animals, and utilize the multiplication of matrices that offer output to help with the training process. Convolution is the name given to this procedure. By altering the size of the kernels and concatenating their outputs, multiple-size patterns can be detected. Output is a feature map or dataset output filter. The procedure can be presented graphically. (Asha and Meenakowashalya 2021).

R.N.N uses sequential data processing to train data in order to learn. Memory retention is confirmed by the sequential process. Recurrent neural networks are sometimes referred to as long-term dependencies in the training data for the learning process since the outcome from one iteration is utilised by the input from the next iteration. L.S.T.M cell made up of weights and three distinct gates for training the learning data. input gate for the current input, output gate to predict values, and a forget gate are employed at each step to reject extraneous information. (Asha and Meenakowashalya 2021).

IV. Results And Discussions

A. One Class (SVMs)

One Class SVM is used to generate learning models with a single class (label) of dataset, and the learnt models are then used to predict the labels assigned to the testing data with both of the labels in a dataset. The findings of the experiments were then presented, analyzed, and interpreted (Table 1 and Fig 2).

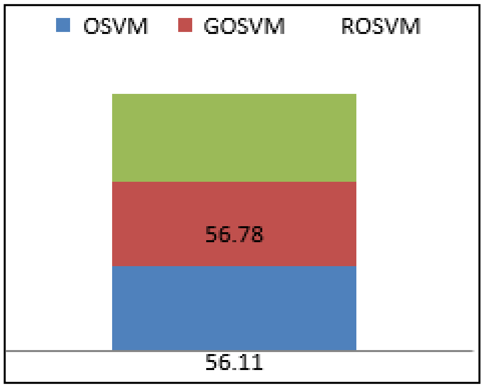

Fig. 2. Comparative Analysis of SVM Classifiers

Table II. Performance Metrics of SVM Classifiers

Accuracy of OSVM	54.67
Accuracy of OSVM with Grid Search CV	56.11
Accuracy of OSVM with Random Search CV	56.78

B. MultinominalNB, Logistics Regression, Decision Tree, Random Forest, Gradient Boost, SVM and KNN

The study was done on the Count Vectorization feature extraction method and then, the size of n-gram increased to 4 from 1. Also, the number of features ranging was 1,000 to 50,000.

The results achieved through the experiments shown in Figure 13, the highest accuracy was achieved is 99.3% throughout the whole experiment on svm and Random Forest techniques. However, rest of the techniques achieved good results too. However, amongthe other classifiers, SVM had the highest average accuracy. Figure 8 depicts the SVM classifier's confusion matrix. The maximum accuracy reached by s.v.m, which achieved 99.3%. and the highest average accuracy of 99.13% throughout the whole experiment. The study recommends that SVM provides the best of accuracy for this particular case study and dataset among all classifiers, because of its higher accuracy achieved.

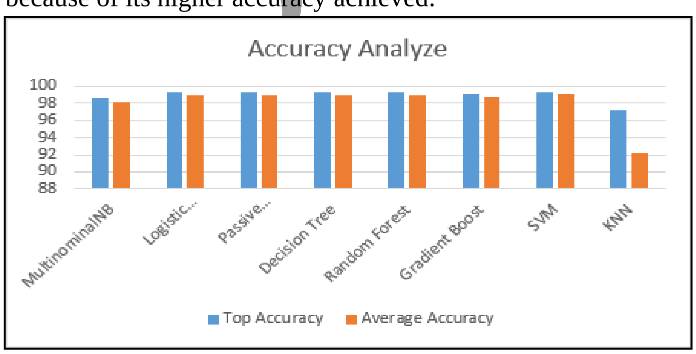

Fig. 3. Accuracy Analysis of each Classifier

The results achieved through the experiments shown in Figure 3, the highest accuracy was achieved is 99.3% throughout the whole experiment on “Random Forest and Support Vector Machine “techniques. However, rest of the classifiers achieved good results too. However, among the other classifiers, SVM had the highest average accuracy. Figure 4 shows the confusion matrix produced by SVM classifier.

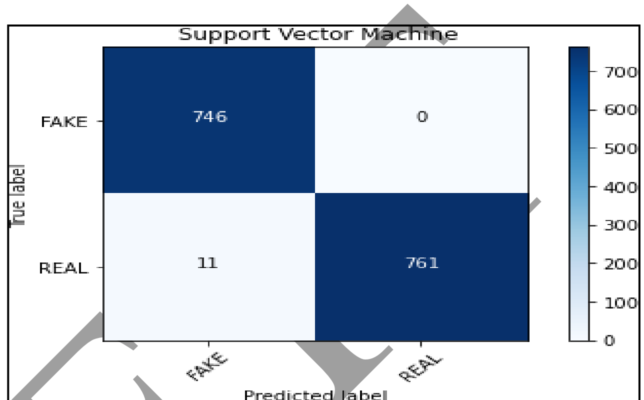

Fig. 4. Confusion Matrix of SVM

V. CONCLUSION

Due to the increased use of online resources, spreading fake news has become much easier. Many people are continuously connected to social media platforms and the internet. Concerning the broadcasting of news on these platforms, there are no limitations. As a result, some people exploit these platforms and start spreading false information about persons or organizations. This might harm an individual's reputation or a business's reputation. People's opinions about a political party might also be affected by false news. A mechanism for detecting fake information is required. Classifiers based on machine learning are used for a wide range of purposes, including detecting fake news.

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