



# Identification of Fake News through SVM and Random Forest

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## Abstract:

There seems to be increasing issue in recent years that disinformation on social networks is harming communities and institutions of democracy. In turn, steps have been declared by social networking sites to restrict the dissemination of fake news. The widespread of false content has the capacity to have highly negative effects on people and community. Consequently, identification of false information on social media is an evolving science now a days that is drawing great attention. False content identification on social networking sites poses specific features and obstacles that render current detection techniques unreliable or not relevant to conventional media outlets. A latest research upsurge in this field is to solve major aspects utilizing data augmentation, algorithm extraction and information-based patterning. Classifying how fake content from social media propagates and why it is effective in misleading viewers are important for creating effective identification techniques and algorithms for primary prevention. **In this work, fake news detection is performed using two proficient algorithms Support Vector Machine (SVM) and Random Forest on text based dataset of Kaggle. When it comes to comparison, Random forest yields better outcome than SVM which is proved by the carried out work.**

**Keywords:** Fake news, Social networking sites, Support Vector Machine (SVM), Random Forest, Text based dataset.

## I. INTRODUCTION

Growing proportion of human lifestyles are spent communicating. Yet more people prefer to check over and access social networking updates online via social media channels instead of formal structures for news. The widespread distribution of false news could have a significant adverse effect on people and economy. Initially, false news may result in breaking the equilibrium of reliability in the network of news. Fake news identification on social networks raises a range of modern and complicated issues in science. Although false content alone is not a totally new question, groups or nations have used the news media to carry out agitation or to manipulate activities to increase in social web-generated media news for decades has made false information a more effective potency that confronts standards in media. Social networking becoming increasingly prevalent, increasingly people access news from social media rather than conventional media of news. Social networking is being utilized to distribute false news with major adverse effects on specific users and culture at large. On many types of blogs, fake content originate. For instance, certain websites are completely set up to post articles that are purposely manufactured and inaccurate. To represent that of recognized media sources, the identities of these pages are also selected. Some humorous websites offer posts that, when viewed outside from scope, could be perceived as accurate. The total expenses of accessing the marketplace and generating material is exceedingly minimal on social networking sites. This tends to increase efficiency of both the short-term and small-scale tactics frequently implemented by fake media publishers and decreases the perceived value of gaining a brand for reliability over the long run. The social networking sites style, thin strips of data displayed on smartphones or web page screens, will make it complex to determine the factuality of a post. In the modern world, it is seen that incorrect data has had a huge effect on economic growth, impacting the reaction to environmental hazards and terror acts. The effect is evaluated on the social web as the participation it creates from its subscribers, utilizing measures like the quantity of views, the

amount of days it persisted without even being deleted, or the majority of participants it penetrated from shares. Utilizing interaction tactics like total views, sharing count, the effect of fake content on the website is calculated. Analysis has also depicted that although most misleading news is not efficient, a tiny proportion is greatly effective, increasingly prominent bits of fake data draw more attention than actual facts, and fake news spreads quickly and rapidly around the network and enters a wider social networking populace. This work is implemented for the purpose of identifying fake news on social media through SVM and Random forest. The text based dataset from Kaggle website is used to detect the fake news. Accuracy comparison is done for the two algorithms.

## II. LITERATURE SURVEY

Jiawei Zhang et. al., [1] presented the difficulties identified from the determinant factors of false information and numerous associations between news reports, authors and topics. This work proposes a new automatic model of false information legitimacy. It constructs a profoundly diffuse framework to study the interpretations of news reports, authors and topics concurrently on the basis of a collection of specific and implicit feature vectors by the textual content. False information refers to the kind of daily mail that deliberately displays misleading data or fake stories propagating by both the conventional print media and latest social networks online.

Aswini Thota et. al., [2] evaluated the approach by utilising Deep Learning algorithms for the purpose of false information detection. The accelerating growth in the production and transmission of erroneous media introduces an instant demand for certain distorted news stories to be tagged and detected instantaneously. Accurate analysis of false information is a difficult task to achieve as it needs the method to recognise complexities in natural language. False news is a concept used by conventional news sources such as tv advertising, and also non - conventional news sources such as social networks, to reflect false news or advertising that contains misleading data. The basic purpose for propagating

this information is to confuse viewers, harm some individual's reliability, or benefit from headlines.

Steni Mol T S et. al., [3] analysed the systematic overview of studies in current survey on the identification of false information on the internet. A huge amount of data has been exchanged on social networking websites and we are unable to distinguish as to which data is false and which is true. When they come along a message, users instantly begin communicating their complaint or voicing their viewpoint, before checking its validity. It therefore leads to its distribution. The much more common sources of incorrect and unauthorised data are false information and rumours and must be identified quickly to prevent their drastic issues. This work introduces the social networking false news identification study, which would be to determine the public view of a customer's different forums and to detect the real facts. Research focus on identification of fake news confirmed by using different strategies of computer vision and machine learning.

Veronica Perez-Rosas et. al., [4] Concentrate on automatically detecting false news in digital media. Their effort is a dual one. Initially, they are launching two additional repositories comprising seven separate content sources for both the purpose of spam identification. They outline in depth the method of compilation, interpretation and confirmation and provide numerous empirical research on the detection of language groups in the context of false and legitimate information. Secondly, in order to create accurate false information indicators, they perform a series of training observations. Furthermore, empirical reviews of the automated and manual recognition of false information are given. Fake media identification has attracted great interest from the wider populace and scholars as the distribution of fake data online upsurges, specifically in news organizations like social networking accounts, news casts, and internet publications.

Monther Aldwairi et. al., [5] developed a system that users can utilize to identify and select out pages consisting fake and manipulating content. To accurately recognise fake stories, they use easy and deliberately chosen attributes of the name and message. The concept of false information is not a new thought. Particularly, long before the advent of the web technology, the concept persisted because newspapers used inaccurate and deceptive data to advance their objectives. Even more customers started to forsake the conventional media outlets used to spread data for internet networks since the emergence of the internet. So does the above option permit users in one session to browse a range of articles, but it is much more convenient and quicker.

Julio C. S. Reis et. al., [6] discovered many kinds of features derived through news articles, comprising social media outlets and posts. Furthe to explore the key elements suggested for false information detection in the research, they introduce a novel collection of features and test the estimation efficiency of recent methods and automated spam identification features. Their findings show significant aspects about the utility and value of fake news identification features. Finally, they explore how false news identification strategies can be utilised in reality, illustrating problems and possibilities. News sources may use automated false information identification as an additional method for determining material which would be more inclined to be false. Their findings indicate that, coupled with current classification models, the estimation efficiency of selected models has a relevant range of selective power for identifying fake news.

Pallavi B. Petkaret. al., [7] conducts a review of deep learning methods, which are primarily utilised for fake identification and are easier to produce outcomes. For many factors, identification of misleading facts is technically difficult. Information is generally produced and rapidly shared using different social networking platforms, resulting in a huge amount of data to be analysed. Internet data is quite common, covering a vast range of topics, adds difficulty to this mission. for the identification of false information coming from noncredible sites that distort actual news articles, the integration of deep learning algorithms is examined. The goal of the research is to figure out a solution that people can utilize to identify and select out pages that consist false and inaccurate information.

False information purposely confuses public into supporting fake data and changing the reaction of public to the true one. Depending on their content, it is harder to identify generated false information as this language being utilized in fake data is very similar to the language being used in real news, as false information is generated with the intention of being accepted. Therefore, identifying false news on social networks has some complicated survey issues.

M.Sowmya et. al., [8] premised on an interface-oriented way to examine the latest false information problems. Details and data accessible on reputable sites of the public interest as well as different portals are used to formulate questions for review. Conventional media contains mostly of individuals who decide what does and will not be composed and transmitted. In this modern age of social networks and styles, the production and distribution of articles and information is complex in our culture. A substitution pattern has been the rapid conversion of traditional media into web plat forms. Instead of traditional media outlets, more people hoard information from web based lives. As always, web-oriented life has also been used to disseminate fake news, which impacts distinguished people and culture. An innovative framework for fake news identification using deep learning algorithms is shown in this work.

### III. PROPOSED SYSTEM

The proposed work is to collect the dataset, pre-processing the dataset and applying machine learning algorithms to it. The below figure 1 shows the architecture of the proposed system.

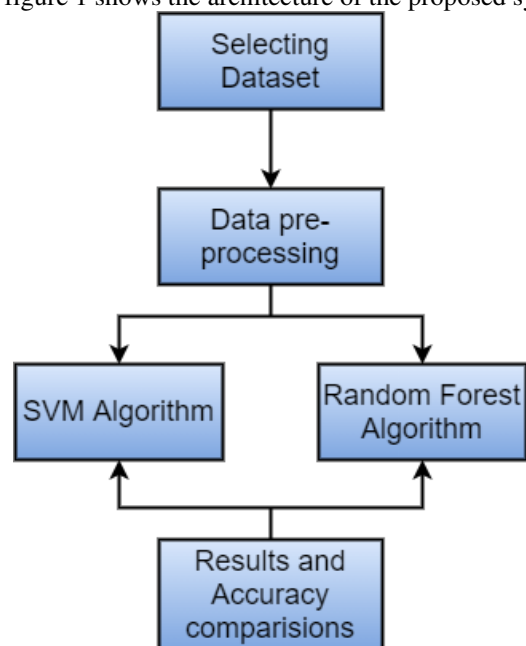


Figure.1. System architecture

### 3.1 Data pre-processing

Raw content needed certain data pre - processing before they could be fed into the simulations. Data Pre-processing is a method for data exploration that converts original data into a suitable form. Actual data (real life data) is often inaccurate and therefore could not be sent over the design with that information. This may cause some mistakes. So while we send over a system, we have to pre-process data. The measures that were taken are:

- Importing libraries
- Data-set imports
- Have a look at the missing values
- Check the categorical values
- Dividing the data set into test and training sets
- Scaling of Functionality

### 3.2 Support Vector Machine (SVM)

SVM is a supervised algorithm of machine learning. The optimum feature space is found by the SVM, enhancing the margin. A point, 2D line, 3D plane, 3D + hyperplane is a hyperplane in 1D. By considering a hyperplane and measuring its distance between the vectors, the margin is measured and then doubled. The SVM algorithm working is shown in figure2.

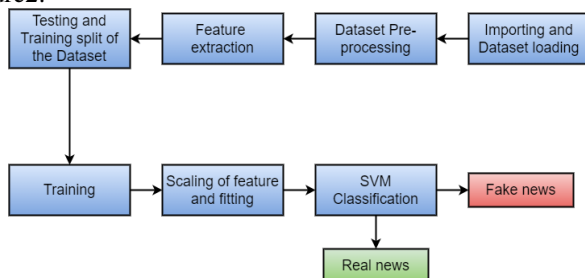


Figure.2. SVM Algorithm

#### SVM works by incorporating below steps:

- Dataset loading: The dataset in .csv form and is loaded into the R integrated design framework Studio via the GUI. The text-based dataset is taken from the Kaggle website. 250 entries and 22 attributes are available.
- Data pre-processing: The framework must first make certain improvements to the current data while visualizing the data utilising the n-gram system and applying features to it, including eliminating punctuation and stop terms, translating all the data into lower cases. This aids to concentrate only on the real data that offers more details than the data which only introduces uncertainty to the system.
- Function extraction: The most challenging task is the primary explanation behind the classification accuracy. Insignificant data will decrease the classifier's efficiency and accuracy. Therefore, prior processing the characteristics, it is easier to delete the useless information. Two classification methods are used to analyse the system: Term Frequency (TF) and Term Frequency Inverse Document Frequency (TF-IDF) for selecting the features associated with dataset.
- Training and testing Dataset split: The suggested method makes use of the most popular method of dividing to divide the data into training and test sets, which is 20 percent for testing and 80 percent for training.
- Scaling of feature: There is a need to conduct feature scaling for SVM classifier to function effectively. Feature Scaling is a strategy used in a specified field to standardise the individual features available in the information. The standardisation of features makes the values of every function null-mean (while the mean in the numerator is subtracted) and unit-variance in the results.

•SVM Classification: After the data has been effectively trained, the method is used to evaluate unlabelled data with the testing information to uncover out if it is false or true.

### 3.3 Random Forest Algorithm

Often referred to as Random Decision Forests, Random Forests may be used for classification and regression issues. This may also be used in the unsupervised approach. The Random Forest technique was introduced by Brieman. Predictions of several trees are combined by random forest classifiers. Many decision trees are built by the random forest algorithm. Utilizing a subset of features, each decision tree is created. Each decision tree produces one class and eventually bootstraps the votes to obtain the better accuracy from the Random Forest technique. A tree-shaped pattern is used to describe the plan of action in decision tree. At any node, a decision will be made. The below steps are followed:

- Divide the data in a way that the gain of data is maximum (Gain is the calculation of entropy reduction upon dividing).
- The state at a node is chosen, offering the maximum gain for dividing.
- Split is done until entropy exceeds zero.
- To build several decision trees, the above process is repeated and eventually a class is chosen for a sample depending on significant voting.

## IV. RESULTS

The text-based dataset has been found from kaggle website. There are 250 entries and 22 attributes. Attributes are text, creation time, retweet count, favorite count, source, length, user id, user screen name, user name, user created at, user description, users followers count, user friends count, user location, user status count, user verified, user url. The dataset sample is shown in figure 3.

Unique ID/text	retweet_count	favorite_count	source	length	user_id	user_screen_name	user_name	user_created_at
1 Hurricane	0	1	Twitter for iPhone	90	8.80E+17	itsabinakelley	Erica Kane	28-06-2017 22:37
2 Students f	0	0	SocialNewsDesk	132	18813355	WAOW	WAOW	9/1/2009 20:11
3 Harvey cal	0	0	Buffer	112	2.72E+08	HOumanitarian	HOUMAN	26-03-2011 05:33
4  added a	0	0	Google	89	33600664	gdubb79	Gabriel W	20-04-2009 17:58
5 DWF busi	0	0	Twitter Web Client	97	18440701	TexasAmerica	TexasAm	29-12-2008 03:03
6 Stories of	0	0	Twitter Web Client	138	4.11E+08	CelloMomOnCars	CelloMom	13-11-2011 01:57
7 9 Weeks A	0	0	Twitter Web Client	81	2.57E+09	ChefCrayCafe	TrumpAp	13-06-2014 13:34
8 @BestFrie	0	0	Twitter Web Client	144	3.09E+08	cburgessDDH	Christian	31-05-2011 18:00
9 Companie	0	1	Twitter for iPhone	139	5.37E+08	PittBusinessRev	Pitt Busin	25-03-2012 21:06
10 The Energ	1	0	Twitter Web Client	107	74014041	GaltsGirl	Michelle R	14-09-2009 00:30
11 Hurricane	0	0	SocialOmph	87	28606058	earthscrft	Earthscrft	3/4/2009 17:10
12 @eshimes	0	0	Twitter for iPhone	127	9.23E+17	Texaskookster	Miguel Fe	25-10-2017 20:04
13 How Otis	1	2	Crowdfire - Go Big	108	2.03E+08	agunner	Gunner	15-10-2010 12:45
14 Jobs repos	0	0	Twitter for Android	121	47673131	confusedabout	D	16-06-2009 16:50
15 @Charity	0	0	Twitter Web Client	140	7.97E+17	DerrickChubbs	Derrick Ch	10/11/2016 1:43
16 12 nonpr	0	0	Twitter Deck	117	36369382	SAAFdn	San Anton	29-04-2009 14:27
17 Hurricane	0	0	dhvr.it	78	85842228	LakeJacksonTX	City of Lak	28-10-2009 15:33
18 Bonfire W	0	1	Twitter Deck	140	5.66E+08	BonfireWings	BonfireW	29-04-2012 00:43
19 Hurricane	1	0	Mobile Web (M2)	100	8.84E+17	NotFake_News	Real News	10/7/2017 14:45
20 super bow	0	0	Twitter for iPhone	88	3.31E+09	hailey_bazan	Hailey Baz	11/8/2015 23:31
21 Congrats	0	0	Twitter Web Client	123	2.54E+08	OlympicSystem	Olympic R	18-02-2011 06:13

Figure.3. Screenshot of Dataset

Graphical User Interface is created using shiny package in R. There is a side panel to access the dataset. Main panel consists of output of algorithms. Outputs are accuracy, confusion matrix, decision tree. GUI home page is shown in figure 4.

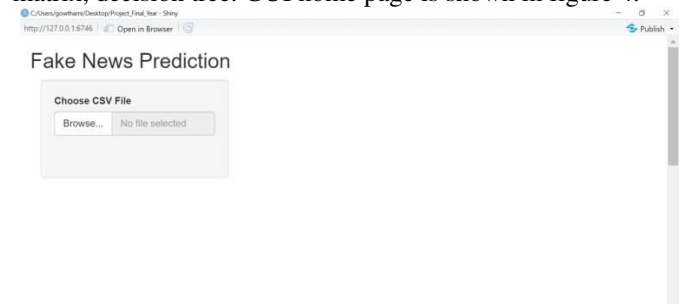


Figure.4. GUI to access csv file and to check the results



Confusion matrix is computed to visualize the performance of the both the algorithm. It is depicted in below figures. Figure 5 shows the confusion matrix for SVM algorithm. Figure 7 shows the confusion matrix for Random Forest.

#### Confusion Matrix SVM

```
tweet_svm_prediction2 FAKE REAL
FAKE 7 6
REAL 9 28
```

**Figure.5. Confusion matrix for SVM**

The result for accuracy of both the algorithms is depicted in figure 6 and figure 8. Figure 6 shows the accuracy of SVM algorithm and figure 8 shows the accuracy of Random Forest.

#### Accuracy

```
[1] 0.7
```

**Figure.6. Accuracy of SVM**

#### Confusion Matrix RF

Cell Contents				
				N
			N / Col Total	
Total Observations in Table: 50				
predicted \ actual	FAKE	REAL	Row Total	
FAKE	16	1	17	
	1.000	0.029		
REAL	0	33	33	
	0.000	0.971		
Column Total	16	34	50	
	0.320	0.680		

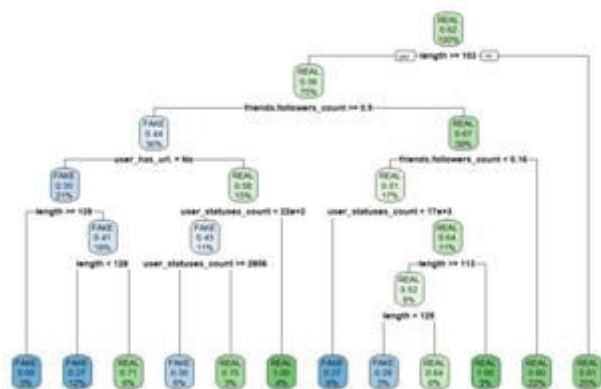
**Figure.7. Confusion matrix for Random Forest**

#### Accuracy

```
[1] 0.98
```

**Figure.8. Accuracy of Random Forest**

The decision tree for Random Forest is obtained from the results which is shown in below figure 9. At the top it is the total probability, it is showing 0.62 is the probability of real news. If length is less than 103, move to root's left child node, it is depicting 75% are length < 103, and probability of real is 0.56.



**Figure.9. Decision Tree representation**

## V. CONCLUSION

The proposed work shows working of two machine learning algorithms namely SVM and Random Forest for the Kaggle dataset to predict the fake news on social media. The accuracy of prediction using the SVM algorithm was found to be 70% and the Random forest algorithm is capable to predict with an accuracy of 98%. After analysis, it is found that the Random Forest algorithm performs better and can be used efficiently for the detection of fake news. The work can be further extended to huge datasets from other websites that contain a greater number of social media websites and networks. Other different algorithms can also be used in combination to achieve a greater accuracy of prediction.

## VI. REFERENCES

- [1]. Jiawei Zhang, Bowen Dong and Philip S. Yu, "FAKE DETECTOR: Effective Fake News Detection with Deep Diffusive Neural Network," 2019.
- [2]. Aswini Thota, Priyanka Tilak, Simeratjeet Ahluwalia and Nibhrat Lohia, "Fake News Detection: A Deep Learning Approach," *SMU Data Science Review*, pp. 1-20, Vol. 1, 2018.
- [3]. Steni Mol T S and P S Sreeja, "Fake News Detection on Social Media-A Review," *Test Engineering and Management*, pp. 12997-13003, 2020.
- [4]. Veronica Perez-Rosas, Bennett Kleinberg, Alexandra Lefevre and Rada Mihalcea, "Automatic Detection of Fake News," 2017.
- [5]. Monther Aldwairi and Ali Alwahedi, "Detecting Fake News in Social Media Networks," *International Conference on Emerging Ubiquitous Systems and Pervasive Networks*, pp. 215-222, 2018.
- [6]. Julio C. S. Reis, Andre Correia, Fabricio Murai, Adriano Veloso and Fabricio Benevenuto, "Supervised Learning for Fake News Detection," *IEEE Intelligent Systems*, pp. 1541-1672, 2019.
- [7]. Pallavi B. Petkar and S. S. Sonawane, "Fake News Detection: A Survey of Techniques," *International Journal of Innovative Technology and Exploring Engineering*, pp. 383-386, Vol. 9, 2020.
- [8]. M. Sowmya and J. Shiva Shankar, "A Survey on Detection of Fake News in Social Media," *International Journal of Research*, pp. 469-474, Vol. 6, 2019.