# Natural Language Processing based Online Fake News Detection Challenges – A Detailed Review

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Abstract— Online social media plays an important role during real world events such as natural calamities, elections, social movements etc. Since the social media usage has increased, fake news has grown. The social media is often used by modifying true news or creating fake news to spread misinformation. The creation and distribution of fake news poses major threats in several respects from a national security point of view. Hence Fake news identification becomes an essential goal for enhancing the trustworthiness of the information shared on online social network. Over the period of time many researcher has used different methods, algorithms, tools and techniques to identify fake news content from online social networks. The aim of this paper is to review and examine these methodologies, different tools, browser extensions and analyze the degree of output in question. In addition, this paper discuss the general approach of fake news detection as well as taxonomy of feature extraction which plays an important role to achieve maximum accuracy with the help of different Machine Learning and Natural Language Processing algorithms.

Keywords—Fake News Detection, Natural Language Processing, Online Social Network, Machine Learning, Sentiment Analysis.

# I. INTRODUCTION

In today's era fake news is a growing challenge. One may describe fake news as news that consists of intentional lies or hoaxes that are spread via conventional news media or online social media. In order to mislead a person or an organization financially or politically, fake news is written and distributed. The propagation and distribution of such false news presents significant risks, including from a national security standpoint from many different perspectives. Authenticity of the social media articles is often not verified. It is necessary to build a system to automatically detect fake news to help reduce the adverse effects of such news. Within the field of fake news identification, a variety of strategies have been suggested to prevent users from becoming victims of misleading social media spreads like a wild fire.

### II MOTIVATION

Detection of a fake news is more difficult than misleading information. Jump-shot Tech Blog reported that 50 % of total traffic of face book referrals accounted to fake news sites whereas 22% of the total traffic are found from genuine sources [23].

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- Several networks use clickbait techniques and phishing to raise advertising profits.
- Fake information can adversely impact both national security and the safety of individuals, and detection of it has become a common problem of cyber-security application layer.
- The algorithms were parsed in the commentary section of each article in view of the validation of fake material. This means that the audience will tell whether a particular article is credible or not to the algorithms. However one cannot completely rely on your audience for this insight as it may cause invariably biased result.
- A dataset of humanly annotated true and false statements cross-checked from data from Wikipedia articles frequently used by researchers in the area of machine learning could also lead to biased data.
- Many of the existing detectors depend on the detection of a text source as a reference to decide if it is fake or real. There are, however, two problems: the same source, whether a human reporter or a machine text generator (neural fake news), might produce articles both truthful and incorrect or misleading. It does not help to differentiate between those two to determine the source of the text.
- Satire, propaganda, hoax, conspiracy, clickbait and misleading or out-of-context information are the different types of fake news shown in the given figure 1.

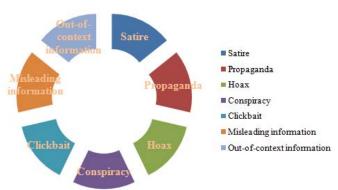


Fig. 1. Different types of Fake News

# III. RELATED WORK

Systematic characterization of the websites, reputation of publisher, age of the website, domain ranking and domain popularity are few important factor considered by Kuel Xu et

al [1]. A tailored dataset is made up of cover news stories from the "New York Times, Washington Post, NBC News, USA Today and Wall Street Journal" have been used as major news outlets. "Ti-idf and Latent Dirichlet allocation (LDA)" topic modeling is used for the analysis of fake news similarities and dissimilarities. Jaccard similarity has been used to differentiate fake and real News, identify and forecast it. LDA however is not an effective approach for identifying or differentiating false or true news in the real world. Instead of comparing the few important words for every new article, Kuel Xu et al., also mentioned exploring word2vec algorithm which would allow embedding of vector and each word to be comparable to typically capture the similarities and differences between the material in the fake and actual news articles.

Fake news detection can also be handled using a cluster based approach, [2] Chaowei Zhang et. al (2019) had proposed a framework that uses cluster based approach. "Kmeans and Affinity Propagation (AP) algorithms" used for clustering process and fake-predicate detection through verb comparison. This method encompasses filters, news that can not be grouped into a cluster or the verbs have a poor degree of resemblance to the verbs in their cluster. TF-IDF is used to derive from feature weights. A tailored dataset is made up various news article from the website sources such as advocate, naturalnews, politico, greenvillegazette and given 91 % as overall average accuracy. However, author mentioned that news category like satire is beyond the scope of this study and could rely on models that are educated in viewpoints and perceptions, advanced methods such as deep learning to build a preprocessing module in real time, using a broad source of fake information from twitter, reddit, facebok etc.

Online news media can targeted along with website verification. However, validating headline of URL for fake news detection is not enough. Sahil Gaonkar et. al. (2019) proposed an approach with different classifier. The various parameters extracted from the URL[3] that include the author, source, post and headline are then passed through various categorizers. The overall result can, however, be improved by site behaviors validation. However, validating site behavior and other related parameters can improve the overall result.

Bi-directional language expression (BERT) model developed by Google has been used by Ye-Chan Ahn et. al (2019) as pre-training model, over a corpus of 1.5 million pieces of data from news and text passage from Korean Wikipedia dataset. A fact corpus extracts a noun or a verb in the news with high occurrence frequency in the preprocessing layer. The input sentence was tokenized by the Relevant Sentence Extractor wherein Word Piece Model (WPM) used as tokenizer (WPM can be applied to all languages) and Fine tuning and prediction is performed using BERT. AUROC curve yield a result of 83.8 %. The author suggested to use New corpus and Wikipedia data to improve flexibility as this model unique to Korean data set also corpus in the colloquial form frequently used in SNS should be learned in detail [4]. Evaluating n-gram properties and word embedding can be effective way to detect fake news. Hrishikesh Telang et. al. (2019) used GloVe vectors with neural networks. Leaky ReLU activation feature used to

provide high accuracy for input classification. Open source dataset was used here, randomly selected 10,000 papers from the dataset and marked '0'. A further group of 10,000 papers were chosen from a Fake News free Kaggle dataset and numbered' 1.' TF-IDF and Global Vectors (GloVe) used for feature extraction. "Logistic Regression (LR), Random Forest(RF), Recurrent Neural Network (RNN), Long Short Term Memory (LSTM), Gated Recurrent Units (GRUs)" methods used with GloVe vectors with neural network have proven the most efficient way to classify fake news article. Accuracy observed in the LSTM is 66 %, for GRU is 66.4 %, for RNN is 71.0 %, for RF is 70 % and for LR is 66.9 % respectively [5].

Detecting tampered images along with the tweet is a challenging task. Shivam B. Parikh et. al. (2019), proposed a framework that uses computer Vision service from Microsoft Azure try to identify text in images and extract recognizable words in a readable format. Customized dataset has been used wherein tweets are collected using Twitter public API. The method was able to achieve upto 83.33% accuracy with increased number of features [6]. This approach is however unable to verify real tweets no longer available because of the removal of that tweet or a tweeting account. Fact checking approach could rely on sentiment analysis for better result [7]. Bhavika Bhutani et.al. (2019) proposed a solution where in sentimental analysis is used. Customized dataset was prepared using different data sets from emergent dataset like kaggle and politifact. In this approach, combination of Naïve Bayes and tf-idf is used to predict the sentiment of the post. The proposed approach was evaluated using LIAR dataset, George McIntire and merged dataset with Naïve bayes classifier and Random Forest classifier.

Jiawei Zhang et al. (2019) discussed the importance [8] of textual information usage about the content and the credibility of the news sources as it has strong with the creators and subject and inference result of fake news. Jiawei Zhang et al., proposed a "Hybrid feature learning unit (HFLU)" for learning the features of news article, creators. The tweets posted on twitter page of PolitiFact and the news published on the it's website are used as data sets. In the proposed model, Explicit and Latent Feature extraction is done and fed as the inputs to the gated diffusive unit (GDU). Each of the creators, subjects and News Articles uses GDU, HFLU and input unit and forms a Deep Diffusive Network model. The accuracy score obtained by the model is 63 % which is 14.5 % higher than Hybrid CNN, LIC, TRIFN. Georgios Gravanis et. al. (2019) proposed Feature Set and algorithm based bench marking pipeline approach. In this study, Naïve Bayes, SVM, Decision Trees, KNN classifier with AdaBoost and Bagging ensemble methods are used. The dataset used here are from "Kaggle EXT (Kaggle with Reuters), McIntire and Kaidmml" so that dataset becomes UNBiased. [9] This study uses content based feature approach that add source and news author metadata, as well as knowledge sharing features of social media, utilizing larger datasets and utilizing deep learning approaches. Taxonomy of spammer detection is discussed based on the ability to detect fake user identification, content, URL-based spam. Faiza Masood et. al. (2019) performed a study of spam detection

strategies on Twitter. Moreover, performed comparison of different feature used for spam detection [10]. Also discussed goals, dataset and experiment result for Anomaly detection based on URL and various machine learning algorithm. Terry Traylor et. al. (2019) proposed an approach with "custom attribution feature extraction classifier" which consider length of the quote, spam of the attribution, enables simple quote attribution and absolute distance of attribution span [11]. Customized dataset of corpus used 40 different online sources and collected 218 documents. The final overall accuracy achieved was 69%. Attribution feature extraction can be combined to identify fake news in future.

Linguistic analysis model on tweets has been used by Amitabha Dey et. al (2018) with customized dataset of "Fake Tweets on Hillary Clinton from Fresh News", TruthFeed, Christian Times Newspaper sources had been used also Credible tweets from Reuters, The Economist, CNN used in the process. Sentiment analysis has been done to expose hidden bias towards the subject and applied k-nearest neighbor algorithm with 66 % accuracy however BoW models will lead to improved accuracy [12].

Zhixuan Zhou et. al. (2019) discussed about Adverse attacks on the deformity, the interchange of objects and creates uncertainty [13]. McIntire's fake-real-news-dataset used in this research containing 6,335 articles. The approach checks several aspect such as title, content and Domain however main focus of this is on linguistic characteristics. The limitation of this method is it's vulnerability and bias towards certain topics in a flawed attack. In the sense of news propagation, a crowd-source information graph can be powerful and prompt however attackers with special intentions have equal access to creating and editing. AI-based systemcan be used with Auto encoder and Recurrent Neural Network to learn users behavior and detect fake news in Sina Weibo with 80.2 % accuracy. Weiling Chen et. al. (2018) used tailored dataset has been made up of number of tweets from Fake news centric dataset and Genuine news centric dataset. The approach proposed several tweet based and comment based features that describes user sentiment and spread pattern using case studies. [14] AI-driven framework AE and RNN will proposed into the users 'usual integrate the features comportments, then conducted a fake news detection at Sina Weibo.

BiLSTM along with Unified Kev Sentence Information does matching of the sentence between key sentences and word vectors of questions. Namwon Kim et. al. (2018) proposed a model that consist of decision, matching representation, context representation, word representation and key sentence layer on the Korean Article Dataset with an overall average accuracy of 69 %. Existing model extracts set sentence however extracting key sentence independently and using deep learning approach can improve the result [15]. Furthermore, Stefan Helmsteller et. al. (2018) used a model with various groups of features including topic, sentiment and text feature, tweet and user level that can be used to boost accuracy. Learning algorithm such as "Naive Bayes, Decision Trees, Support Vector Machines (SVM), and Neural Networks as basic classifiers and two ensemble methods i.e., Random Forest and XG-

Boost". Using these approaches achieved F1 score of 0.77. The dataset includes around 4 lacks examples among these 27.6% are from sources with the fake news, while 24,4% are from trustworthy sources and during collection categorized tweets whether they are from trustworthy sources or not [16]. Zaitul Iradah et. al. (2018) proposed a mechanism with hybrid, context and content based approach. In the content based approach following features are considered visual based and knowledge based method, style based deception detection, text representation, Linguistic cue. Stance and propagation tree kernel based methods are used in Social context-based [22]. 87 % is achieved by style based method and visual based achieved 83.6 % accuracy. [17] In future, Visual feature and network feature can be covered widely to achieve greater accuracy.

Modified CNN has been used by Youngkyung Seo et.al. (2018) that uses the MNIST dataset, second is the refined one collected from 16 medias and media dataset, model modification, batch size control and data augmentation are few important points considered in model with 75.6 accuracy [18]. Saranya Krishnan et. al. (2018) proposed a generalized framework to predict tweet credibility [19]. Dataset containing hurricane sandy, containing only miscellaneous and combined both are used. User feature and content features are extracted. J48 and SVM algorithms are used and achieved 80.68 for hurricane sandy and 81.25 % for Boston Marathon using J48 tree. The crowd sourcing data collected and saved in Dynamo DB can be used to feed into the algorithm design and re-raining of the classifier to further boost the framework. Using a statistical models to classify social network user behavior and leverages anomaly detection to recognize unexpected behavioral changes. techniques Manuel Egele et. al. (2017) used 1.4 billion messages from twitter, 106 million messages from facebook as a dataset. COMPA builds a social network user activity profile that identifies user vulnerabilities based on past account messages. Each time a new message is produced the message is compared with the behavioral profile. An attacker aware of COMPA is able to prevent COMPA from identifying its compromised accounts. The attacker may post messages which correspond to the behavioral profiles of the accounts concerned.

## IV. TECHNIQUES AND CHALLENGES

Several approaches have been used for identification of fake news. General approach is to gather data, perform the various preprocessing text operation such as text cleaning, tokenization, handling stop-word and punctuation etc in order to remove the noise in the data. Then extract the features and use with different supervised and unsupervised models to achieve the better accuracy.

Corpus is formed by combining tweets from genuine news centric and fake news centric dataset. However, dealing with spam detection in the corpus and retrieving the relevant tweets is an essential task. An additional pre-processing is needed in this situation. The performance of a text classification model is highly dependent on the words in a corpus and the features

created from those words. To analyze and model the data further, it has to be converted into features. Techniques may include bag of words (BOW model), tf-idf or Glove model. In order to achieve the better accuracy basic classifier model such Naïve Bayes, Logistic Regression, Decision Tree, Support Vector Machine, Multilayer perception techniques or ensemble method such as Random-Forest and XG-Boost are used. Deep learning based techniques are also more popular. AI has proven to be a multi-faceted tool for detecting false information because a significant amount of the data can be analyzed rapidly. Table I provides here a comparative summary of different Machine Learning and Natural Language Processing algorithms, dataset used by researchers along with the methodologies and challenges with accuracy however Figure 2 shows the general approach used in the fake news detection process.

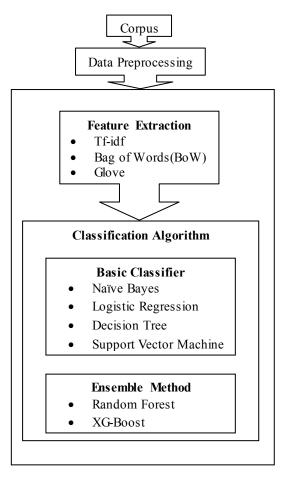


Fig.2. General Approach for Fake News Detection

TABLE I. TECHNIQUES AND CHALLENGES

| Technique        | Accuracy | Dataset      | Methodology  |
|------------------|----------|--------------|--------------|
| _                | -        |              | & Challenges |
| (tf-idf) and     | -        | Cover news   | Explore      |
| Latent Dirichlet |          | stories from | word2vec     |
| Allocation       |          | major news   | algorithm    |
| (LDA)            |          | outlets      |              |
| modelling        |          |              |              |

| Technique                       | Accuracy                   | Dataset                         | Methodology                     |
|---------------------------------|----------------------------|---------------------------------|---------------------------------|
| CNT,                            |                            |                                 | & Challenges<br>Models          |
| AHGNA and                       | 01.00/                     | Fake and                        | trained in                      |
| proposed                        | 91.9%                      | valid articles                  | opinions and                    |
| FEND<br>(K-means and            |                            | from website sources.           | perspectives<br>should be       |
| AP)                             |                            | sources.                        | focused.                        |
| Naïve Bayes,                    | ND 74.0/                   | Facebook news                   | Validating site                 |
| Logistics<br>Regression,        | NB- 74 %<br>LR-77.2 %      | postsT witter                   | behaviour and other related     |
| SVM, Multi                      | SVM- 82%                   | post Dataset by<br>BibSonomy.or | parameters can                  |
| Layer                           |                            | g g                             | improve the                     |
| Perception                      |                            |                                 | result. As this model           |
| BERT                            |                            |                                 | specific to                     |
| (Bidirectional                  |                            | Corpus of 1.5                   | Korean                          |
| Encoder                         | 83.8 %                     | million news data, , specific   | dataset, new corpus and         |
| Representations<br>from         | 03.0 70                    | to Korean                       | Wikipedia                       |
| Transformers)                   |                            | dataset                         | data to                         |
| ,                               |                            |                                 | increase<br>versatility         |
|                                 |                            |                                 | Deep learning                   |
| LCTM                            |                            |                                 | techniques alo                  |
| LSTM,<br>GRU,RNN                | LSTM- 66 %                 |                                 | ng with the Le<br>aky ReLU acti |
| RF, LR With                     | GRU- 66.4 %<br>RNN- 71.0 % | Open source<br>Signal Media     | vation feature                  |
| TF-IDF and                      | RF-70 & LR                 | News Dataset                    | and Glove                       |
| GloVe Feature<br>Extraction     | 66.9 %                     |                                 | Vectors<br>used to              |
| 2                               |                            |                                 | provide high a                  |
|                                 |                            |                                 | ccuracy.                        |
|                                 |                            |                                 | The proposed system             |
| Uses Computer<br>Vision service |                            | Tweets                          | provides false                  |
| from Microsoft                  | 83 %                       | collected                       | positive                        |
| Azure to detect                 | 83 70                      | using Twitter                   | results by<br>deleting          |
| text in an OCR image.           |                            | public API                      | tweets or by                    |
|                                 |                            |                                 | tweeting an account.            |
|                                 |                            |                                 | Different                       |
| Random                          |                            | LIAR dataset                    | neural network                  |
| Forests, M-                     | 81.6%                      | Kaggle dataset                  | algorithms can<br>be used to    |
| Naive Bayes                     |                            | PolitiFact                      | enhance the                     |
|                                 |                            |                                 | accuracy.  A model has          |
| Learning using                  |                            |                                 | incorporating                   |
| Network                         |                            |                                 | Knowledge                       |
| structure of<br>News articles,  | 63%                        | T weets posted by PolitiFact    | on the<br>network               |
| creators and                    |                            | by Fonthact                     | structure into                  |
| news subject                    |                            |                                 | model                           |
|                                 | KNN 0.921                  |                                 | learning,                       |
|                                 | Bagging                    |                                 | Uses an                         |
| KNN                             | 0.944                      |                                 | approach focused on             |
| Decision Tree<br>Naive Bayes    | AdaBoost<br>0.949          | Kaidmml,<br>McIntire,           | content,                        |
| SVM                             | SVM 0.950                  | Kaggle-EXT                      | adding the                      |
| AdaBoost                        | Naive Bayes                | £                               | news source<br>metadata and     |
| Bagging                         | 0.881<br>Decision Tree     |                                 | news author                     |
|                                 | 0.858                      |                                 | info.                           |
| Da is C                         |                            |                                 | Detection of                    |
| Review of<br>Twitter Spam       |                            | Tailored                        | spam and<br>anomaly             |
| Detection                       | -                          | dataset                         | detection                       |
| Techniques                      |                            |                                 | based on URL<br>and use of      |
|                                 |                            |                                 | and use of                      |

| Technique  | Accuracy  | Dataset   | Methodology<br>& Challenges   |
|--|---|---|---|
|  |   |   | machine<br>learning<br>algorithm  |
| Single/double<br>Quote<br>Attribution<br>Identifier &<br>classifier                                      | 69.4  | Customized<br>dataset<br>218 documents<br>from<br>over 40 online<br>sources.                          | Combine<br>attribution<br>feature<br>extraction with<br>emerged<br>factors to find<br>potential false<br>content                          |
| BoW model<br>focused on the<br>labeled<br>classification,<br>KNN   | 66.66 %   | Fake Tweets<br>on Hillary<br>Clinton<br>Source: Fresh<br>News,<br>TruthFeed,<br>ChristianTime         | Perform in-<br>depth stance<br>detection  |
| Linguistic<br>characteristic<br>and crowd<br>sourcing<br>Knowledge<br>graph model.                       | 62.4  | McIntire's<br>dataset   | Build a visualized interface for news knowledge graph crowd sourcing. AI-   |
| Autoencoder (AE) and Recurrent Neural Networks (RNN)   | 80.2 %  | Fake and<br>Genuine<br>news centric<br>dataset:   | driven framewo<br>rk<br>combining AE<br>and RNN and f<br>ake news<br>detection at Sin<br>a Weibo.   |
| Sentence<br>matching<br>through<br>BiLST M   | 69 %  | Korean<br>Article<br>Dataset  | Extracting key<br>sentence<br>independently<br>with deep<br>learning<br>approach  |
| Support Vector Machines, Naive Bayes, Decision Trees and Neural Networks with Random Forest and XG-Boost | best F1 score<br>is 0.78 with<br>both user<br>and<br>tweet<br>features F1<br>score is<br>0.94 | 401,414<br>examples,<br>110,787<br>from fake<br>news and<br>290,627<br>from<br>trust worthy<br>source | Large<br>dataset can<br>give better<br>result.  |
| Context-based,<br>Social Context-<br>based, Hybrid-<br>Based approach                                    | Style based<br>87 %<br>Visual based<br>83.6 %   | Customized<br>data set  | Visual feature<br>and network<br>feature cannot<br>be described<br>extensively<br>because it may<br>be more<br>beneficial.                |
| CNN  | 75.6 %  | MNIST,<br>refined<br>and media<br>dataset   | The potential challenge is the model for fast spreading fake news from various media to incorporate in distributed parallel environments. |

| Technique   | Accuracy  | Dataset  | Methodology   |
|---|---|--|---|
|   |   |  | & Challenges  |
| J48<br>SVM  | 80.68 for<br>hurricane<br>sandy<br>and 81.25 %<br>for<br>Boston<br>Marathon using<br>J48 tree               | Dataset containing hurricane sandy     Dataset containing only miscellaneous     combining both  | Crowd sourcing data may be used to feed into the algorithm design and classifier retraining to improve the performance.   |
| COMPA uses st<br>atistical<br>models to classi<br>fy<br>social network<br>user<br>behaviour,. | The identification of compromised Twitter account by COMPA is subject to approximatel y 4% false negatives. | Tailored<br>dataset T witter<br>dataset consists<br>of 1.4 billion<br>messages,<br>Facebook<br>dataset<br>contains 106<br>million<br>message | An attacker aw<br>are of<br>COMPA is abl<br>e to prevent C<br>OMPA from id<br>entifying its co<br>mpromised acc<br>ounts. |

# V. METHODOLOGIES

The relation between news items, topics and creator trustworthiness infer the outcome of fake news. Classification of fake user accounts can be based on user, tweet, comment, time based and sentiment based feature extraction plays an important role to improve the accuracy of the entire process. Moreover, feature that are based on User are properties and related attributes of the user accounts. Features on tweet are characteristic of the tweet itself. Other user views on the original tweet show comment related features. Content based feature are based on the content. Most news articles are time sensitive so models must process properties of news articles instantaneously. So the models should concentrate on views and viewpoints to attain higher efficiency. The following figure shows the taxonomy of feature extraction.

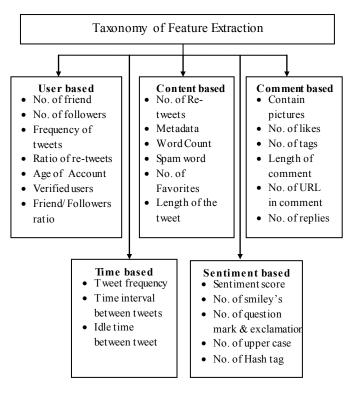


Fig. 1. Taxonomy of Feature Extraction

### VI. MISCELLANEOUS

Along with the different machine learning and NLP algorithm, some of the browser extension and tools provide option to filter spam and notify about untrustworthy sources of news. Table II discusses such extensions and tools with their on click action and methodology.

TABLE II. BROWSER EXTENSION AND TOOLS

| Name of Tool                | Extension/<br>Tool                            | Action  | Methodology  |
|-----------------------------|---|---|--|
| Stop-the-<br>bullshit (STB) | Tool  | Software that<br>blocks spam<br>sites                         | filtering spam   |
| B.S. Detector               | It is an<br>extension of<br>Google<br>Chrome. | Notify about untrust worthy sources of news.                  | Extension's warnings are powered by a list of do mains that are well-known sources of fake data. |
| Fake News<br>Alert          | It is an<br>extension of<br>Google<br>Chrome. | Shows a warning when user visit a website known by fake news. | It relies on a list of<br>fake<br>and misleading<br>news<br>sources                              |
| Faker Fact                  | Firefox                                       | FakerFact uses<br>a machine<br>learning                       | Shares the charact<br>eristics of valid<br>journalism  |

| Name of Tool | E-4 aia : /                                    |   |   |
|--------------|--|---|---|
| Name of 1001 | Extension/                                     | Action  | Methodology   |
| News Guard   | Apple Safari , Microsoft Edge, Google Chrome,  | algorithm trained to detect relevant Fake News patterns.  News Guard is for personal use only and not for | publication, clickbait, conspiracy or satire  Digital news outle ts are researched by seasoned journalists to educate |
|              | Mozilla<br>Firefox                             | commercial  | readers and viewers   |
| FiB          | Tool   | Tests your<br>feed of<br>Facebook for<br>validity of the<br>text, image<br>and url.                       | This tool uses Facebook news feed algorithm that tests the validity of messages.                                      |
| Politi Fact  | Website<br>available in<br>application<br>form | Test the statements made on the Internet by political analysts and politician.                            | The "Truth-O-Meter" app makes it apparent if someone is untrue about the hyperbole sorting                            |

### VII. ANALYSIS

Researching the identification and finding general consensus of fake news is the most common issue in social networks makes the analysis useful. The research in this survey paper has been carried out from 2017 onwards. It has been observed that various standard machine learning algorithm performs well and gives better result compared to other techniques. While the contents of each research are different, the dissemination of fake news is investigated differently, and each is properly evaluated in his / her own area. Deep learning based techniques are more popular AI has proven to be a multi-faceted tool for detecting false information because a significant amount of the data can be analyzed rapidly. For example, in [3], In [14] 401,414 cases, out of which there are 110,787 news outlets (27.6 percent) while 290,627 (24.4 percent) are from reliable source like Reuters news, news from local countries or blogs, authors examined a corpus of 1.5 million posts.

# VIII. CONCLUSION

The purpose of this research was to review, summarize, contrast and evaluate the current research on counterfeit news which includes quantitative and qualitative analysis of counterfeit news and Identifying and Intervening Strategies. As we reviewed, fake news detection is the machine learning solution to deal with the problem of false news, rumors, and misinformation detection. In particular, the composite classification system comprises neural networks consisting of classical classification algorithms, which focus mainly

on lexical analysis of the objects as the main characteristic for prediction and use of external background information.

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