Fake news detection: A systematic review

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***Abstract* - Fake news, misinformation spreads rapidly as the real news thus manipulating public opinion. Fake news represents the false and unsubstantiated details, facts and figures. The uncertain information should be detected promptly in order to minimize its effect. The rapid spread of the fake news has become a matter of concern and has grasped the attention of many researchers for the detection of fake news in order to reduce its impact. During the covid-19 pandemic, there was a high rise of fake news and many researchers have been actively working in this field in order to automate the detection of fake news. This paper propounds a survey on the state of art of fake news detection along with an overview of the publicly available dataset, and fake news.**

***keywords* - Fake news, misinformation, text classification, text mining, deep learning, fake news detection.**

I. Introduction

The emergence of internet technology and the admiration of social media has paved the way for a new channel for the dissemination of the news. Approximately about 65% of the adults in the United States rely on social media for daily news [1]. A substantial amount of unverified and unauthenticated news spreads through social media, web, online forums, etc. misleading a large number of people. During the 2016 presidential election in the U.S., a conspiracy theory now known as the *Pizzagate* was a result of counterfeit news stories on social media [2]. With the advent of the COVID-19 pandemic, there has been a rise in the political and medical misinformation, also known as *global infodemic* [3]. The information spread on the social network floods all the platforms within a small amount of time and usually without any verification of the information [4].

Fake news can be defined as, "to be news articles that are intentionally and verifiably false, and has the potential to delude readers" [5]. Thus, it is necessary to detect fake news circulating on the web and mitigate the problem to build trust with the audience [6]. Social media and online platforms generate and disseminate information every second. With millions of people fraternizing in these social media a huge number of data is generated every second [4]. Opposed to the information through some trustworthy and credible sources, the information spread on these channels is questionable. Thus, to analyze, detect, and mitigate the problem of fake news on different platforms many researchers have proposed various models using various machine learning as well as deep learning algorithms This work includes the state-of-art of various fake news detection algorithms on various platforms.

Though the fake news in the media has been prevalent since the earliest writing system [7], now that the online platforms and the social networks are gaining popularity the spread of these news has increased. The popularity of a piece of information has led to the propagation of the unverified information on social media [8].

The majority of work done by the researchers in the field of fake news detection has been pattern recognition and linguistic analysis, in combining the text mining and text classification, tweet analysis [9]- [11]. The fake news detection algorithm focuses on extracting the features that are embedded in the news content. This paper provides an overview of the state of the art of the technologies and models along with the datasets that are used for analysis of fake news.

The primary contribution of this work is providing an overview of fake news along with the platforms that are used to disseminate the fake news. In addition to that, this paper also provides a summary of the publicly available datasets that has been used for the detection and analysis of fake news detection model, along with the state of art of existing techniques used for fake news detection. The paper is divided into V sections, Section II includes the basics of fake news, section III includes an overview of the datasets, section IV includes a review of the existing techniques for fake news detection and section V comprises of the future scope and conclusion.

II. Fake News Basics

False and unverified information spreads very rapidly, thus amplifying the news and manipulating the public opinion. Fake news characterizes the most popular form of fake and unproven news. Nowadays, with the advent use of technology, the popularity of traditional news channel and papers have comparatively decreased. Most people rely on the internet for the news however the absence of fact checking and verification of the news and its sources gives rise to fake news on these platforms.

This section provides an overview of the fake news cycle, categorization of fake news, the motivation and the platform for broadcasting the fake news along with the impact of fake news and the behavior of user towards fake news.

Fake news cycle

According to global digital report [12] out of the total world population of 7.8 billion, there are 4.5 billion internet users and 3.8 billion social media users. These statistics show that practically half the population rely on the internet for various things. The credibility of the information on the internet is also questionable since most of the news are not verified. Creation, Publication and Dissemination/ Propagation are the three main phases of distribution of fake news, which is shown in Fig. 1.

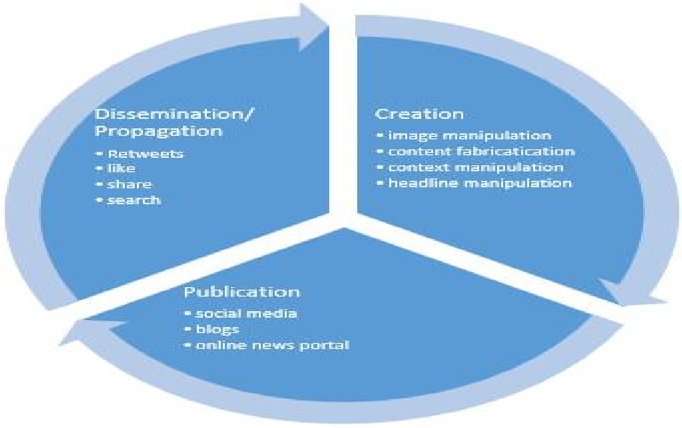

Figure 1 Fake News Cycle

Creation of fake news

Identifying the people behind the fake news and the intention of creation of fake news is still a major concern [13]. The fake news is usually created by either manipulating the image, content or the context of the news or fabricating the content. Political, financial gain and social needs has been identified as one of the major motivations for the creation of fake news [14], [8], [15].

Publication of fake news

With the rise in contents to be published, it is impossible to fact check every information and evaluate the information for possible deception before the publication of the news [16]. Hence, the news is eventually published in various social media, blogging and online sites without the credibility assessment of the news.

Dissemination/ Propagation of the news

Social media is an effective distribution channel for fake news [17]. Social and digital communication networks have proved to be a powerful tool for the publication and distribution of fake news and has also impacted the grip on the traditional news sources [18].

Categorization of fake news

The fake news is present in the form of news content, blogs, image, and video. The different types of fake news are shown in Fig. 2.

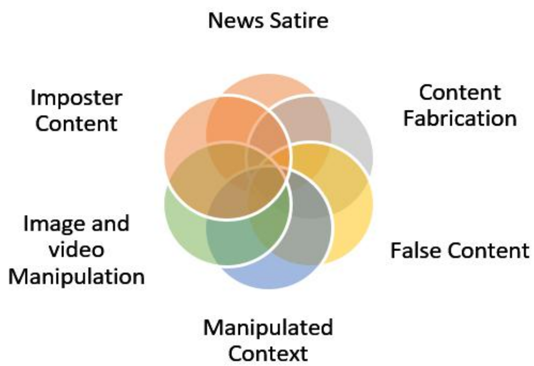

Figure 2. Various types of fake news

News Satire

News satire is the most common type of fake news and can also be referred to as mock news which includes humor and exaggeration of the news [8]. These news articles contribute to shaping public opinion and trust [19]. The satire news usually mimics the original news source which also contributes to creating confusion amongst the people. The satire in the news misleads the people to believe that the heuristics rather than the strength of the argument [20]. The author of the satire news has no intention to harm the people, but the news has the potential to fool the people.

Content Fabrication

A news content that is 100% false. The motive of the producer of fabricated content is to misinform the people regarding a certain issue. Unlike the news satire, there is no interrelationship among the author and the consumer citing that the information is fake [8]. The major issue of fabricated content is not only the format that makes it similar to the real news but also the fact that they are widely propagated.

False Content

This type of fake news is the one where the headline is genuine but the content has no relation to the headline thus misleading the people.

Manipulated Context

The deliberate manipulation of the context of the news to mislead the people to promote a belief, tarnish a person's image, etc.

Image and Video Manipulation

The superintendence of real images and video to create a false version has also been used in fake news [8]. It is usually done by either using a photo shop and photo, video editing tool, or presenting photos that had been taken for a different scenario and different time. Fake images and videos including manipulation of the face that is generated by digital manipulation like DeepFake is becoming a concern for the public [21].

Imposter Content

The genuine source of the news is impersonated in imposter content. The fake news sites mislead the people into believing the fake news in their sites [22]. The ulterior motive of imposter content is to provoke the people for their profit.

Motivation for spreading fake news

Easy access to the information on the web, gives rise to the dissemination of unverified news. The major intention of spreadin g fake news is to mislead people, tarnish the reputation of the people or organization, monetary and political gain.

Political intention:

The fake news has the possibility to taint the public image of the possible candidate, opponent, or promote the candidate.

Financial Profit:

When the fake stories go viral, the content producer generates a certain revenue. Similarly, fake stories and good reviews rega rding a certain product increases its sales.

Promote certain ideology and belief:

During advocating certain ideologies and beliefs, people spread the misinformation and fake news regarding the philosophy, b elief, and person behind the ideology.

Manipulate public opinion:

Since the news has the power to manipulate and change public opinion it is used to manipulate the opinion of the public regar ding various topics.

Entertainment:

A parody of the news is made to entertain the people. Though this type of parody is created without the intention to harm the people, this type of news has the potential to shape public opinion.

Impact of fake news

With the rise in people using social media and the internet, publishing, and distribution of the contents has become more viabl e. Hence, there is also an increase in the proliferation of fake news. Not every reader questions the credibility of the news that they read online, consequently, they believe what they read. The bluffed users on social media has an adverse impact [23]. Fa ke news has the following impact on the society.

- Tarnish the image of a leader or a public figure.
- Fake news can change the attitude of people towards certain brand [24].
- Promotes hate against certain community, religion.
- Spreads hoax and fear in a community.
- Affects people's trust on the news.

Recently, there was a news claiming that the covid-19 test kits were sold in 2017 and the world bank knew about the pande mic [25]. The news was widely shared in twitter, facebook, reddit, Instagram and WhatsApp and people actually believed it. S imilarly, a news claiming that the Oregon wildfire was caused by the fringe groups participating in the anti-racism protest was successful to spread hatred amongst the people [26]. Likewise, a video of protestor chasing a father-daughter duo started surf acing in facebook and twitter leading people to believe that the video is from the Black lives matter protest with huge amount of share and view it had successfully manipulated the people's opinion [27]. Later, it was clarified that the video was from an incident in Portland in the year 2019.

Platform Used to Spread Fake News

The social media platforms have huge amount of users who rely on these media for news and information. Recently, these me dia have also become a home for fake accounts which usually spreads hate, misinformation etc. As of 2019, facebook has aro und 119 million active fake accounts, twitter has around 70 million bots and fake account and Instagram has around 95 millio n fake accounts [28]. These accounts share information and spread un curated topics by using the trending hashtags and topics. Social media: Identifying the veracity of large number of data posted by the users on various social media plat from is a huge challenge [29]. Fig 3. shows the statistics of active users in various social media platforms [30] - [32]. Amongst them many p eople rely on these media for their daily news source.

Facebook: The news in facebook is spread through the wall posts, shares, ads and likes.

Twitter: Twitter allows the user to tweet and re-tweet the popular tweets.

WhatsApp: People using WhatsApp disseminates the misinformation by trusted news outlet like friends and family [33].

Emails: Emails are also considered a platform to consume news, though the validation of the authenticity of the news is cha llenging [34].

Standalone Websites: Many online news sites are found to impersonate the URL and spread fake news. Example: ABCnew s.com.co is a website which mimics the URL of Disney owned ABC.

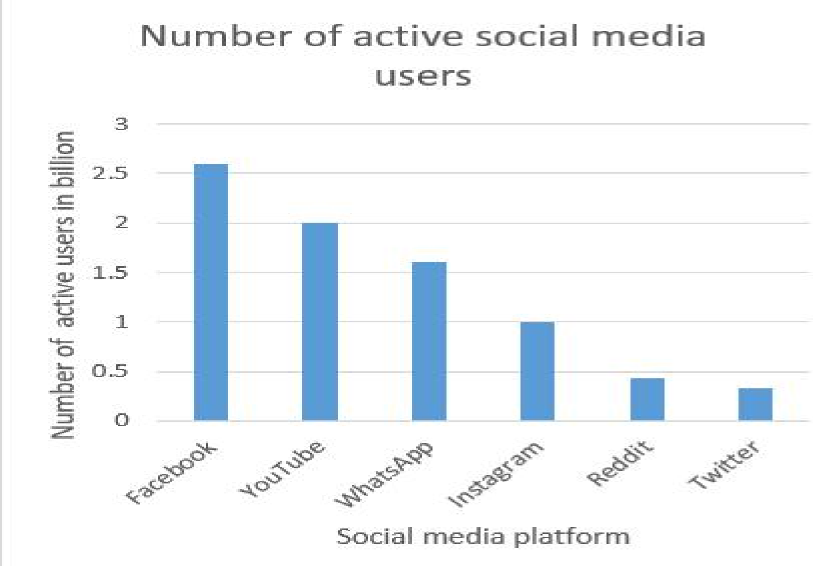

Figure 3. Number of active users on social media

User behavior towards fake news

During a crisis, the frequent use of social networks and the internet by the people is usually to search for relevant posts about the situation, example, according to google, during the covid-19 pandemic, coronavirus was the biggest search topic. A study from flixed released during March 2020, social media are the dominant platform that provide information related to the pandemic. But along with the useful information shared on the platforms, lots of conspiracy theories were also shared which questioned the credibility of these sources for providing information. Articles with headlines like "5G and Covid-19" had people believe the conspiracy theory that covid-19 was the effect of 5G, though scientists had discarded this and informed them that it is spread through droplets and not 5G. This shows that the news without any credible source, shared on the various platforms gives rise to fear, hoax and confusion amongst the people.

Being impacted by fake news, many brands have incurred a huge loss. In the year 2017, a comment by the CEO of snapchat towards the people of India, didn't go down well with the users in India and they uninstalled the app and gave low ratings to the app, but because of some misinformation, and confusion amongst the people, the users gave low ratings and left negative comments for Indian brand snap deal, costing the company its image. According to a survey done with 661 respondents regarding the fake news on Facebook of recall of Dasani water products by Coca cola showed that the consumers perceived the fake news and surpassed their perceived influence on themselves [35].

III. Feature Extraction

Detection of fake news has been done using various approaches including natural language processing and data mining per spective. For the feature extraction, the researchers usually distinguish between two different features; content-feature and con text-feature. The content based approaches depends on features such as texts and linguistic features, whereas, the context-base d feature depends on the user's character, user's feature, social media propagation etc.

Content Feature

Many researchers have exploited the content features for the analysis and discovery of fake news. Content features are generally extracted from text. Linguistic features have been utilized widely used for the purpose of deception detection. Content feature has been considerably studied and implemented for the purpose of fake new detection. Linguistic feature was used to carry out an experiment for deception detection and the experiment showed promising result [36]. Various kinds of content feature that has been exploited for this purpose are semantic feature, syntactic feature and lexical feature.

The semantic feature is usually extracted by employing natural language processing techniques. The semantic feature include s sentiment analysis which adopts the features on the premise emotions of the text. For example, the authors have utilized the content of the tweet in order to detect the [37]. The syntactic feature includes the nouns, verbs, adjectives and the Part of Spee ch (POS) pattern that has been used. The lexical feature is the most straightforward approach used in order to exploit the most relevant content words or expression as a feature [38]. An experiment done to predict the accuracy of rumors in twitter show s that, vulgarity, abbreviation, sentence complexity and average word complexity is very helpful in determining the accuracy of the rumors [39].

Although, content feature has been used extensively for the pretension of detection of fake news, when the content feature i s used in real world application it does not give satisfactory result due to limited generalization of the feature. Similarly, since fake news are becoming more analogous akin to the real news in terms of content, writing style etc. it has become difficult to detect the deceptiveness through the text.

Context Feature

Context features are extracted by mining useful data from the social media posts or the articles regarding fake news. The context feature is usually concerned with the features of the user, source of the rumor and platform used to spread the news and the reaction of the users towards the fake news.

The user based feature comprises of the relevant information of the user including the information about the number of friend or follower the account has, the age of the account along with the number of posts in the account. User based feature has also been used for the differentiation between the fake and the genuine news. Many researchers have exploited the user feature in order to determine the fake news [40] - [41]. Similarly, many studies also consider the use of url in order to detect the fake news [42]. Context feature has been beneficial for detecting the fake news. The verification of an account in social media has been used as a measure to deter the spread of fake news.

The network based feature normally consists of the pattern by which the news disseminates. This feature considers how the post has been shared, the number of retweets and share the post has. The network based feature is infrequently exploited for the intention of fake news detection.

In most of the studies the researcher has incorporated both the user based feature and the content based feature in order to rummage the unverified news.

IV. Data Collection

The collection of relevant data for fake news detection, is one of the challenging tasks. With the large quantity of data on the web it is difficult to manage and fact check each and every information for its credibility. Hence, given the different types of works done by the researchers, in this field, due to which different datasets and data repositories are publicly procurable. This section provides an overview of the publicly available datasets. Different formats of datasets such as headlines, url, text, news article, users comment are used for the analysis of fake news. Twitter API has been used widely for the collection of data in order to analyze the fake news [40]. A detailed description of ways to collect, access and store data using the twitter, facebook and weibo api has been put forward by the authors [43].

Liar Dataset

Liar Dataset is a bench mark dataset for detecting fake news, published by William Yang [44]. The dataset has been extracted from Politifact API and is pre divided into the training data set, validation data set and testing data set which consists of 10269, 1284 and 1266 data respectively, hence the splitting of the data for training, testing and validation can be avoided. The liar dataset consists of six different labels, namely True, False, Half-True, Barely-True, Mostly-True and Pants-Fire. In a quantitative analysis done, it has been found that the labels of the classes often get confused with the other labels [45].

ISOT dataset

The ISOT fake news dataset is a dataset proposed by the ISOT research lab of University of Victoria. It consists of two types of articles true and fake news. It contains two csv files, namely fake.csv and true.csv. The dataset is useful for testing linguistic methods.

Fake News Net

Fake News Net is a data repository of unverified news which consists of the buzzfeed and politifact fake news data. The buzz feed fake and real news consists of 92 data each and politifact has 124 data each. These dataset collects information from news content, social context etc.

CoAid Dataset

To help researchers fight against the covid -19 misinformation, CoAid dataset was published [46]. The CoAid dataset includes 3235 news, 294692 related user engagement and 851 posts related to covid-19.

Pheme Dataset

Pheme dataset was developed by the university of Warwick [47]. The data was collected by using twitter's streaming API. The Pheme dataset is basically a dataset for rumor verification and veracity classification. It consists of rumors influenced by 9 events and consists of the labels: true, false and unverified. It contains 330 twitter conversations.

CREDBANK

The credbank dataset was generated by collecting tweets using, twitter's public data stream and it is the only data set which allows the user to perform analysis on the twitter data [34]. The dataset contains the linguistic, user and network feature but lacks the visual feature.

V. Fake News Detection Approach

Various approaches proposed by the researcher, views fake news detection as a classification problem and associate the particular piece of news with real or fake news label. Many researchers, have implemented either the machine learning or deep learning approaches to achieve the desired result. Similarly, other researchers have also used other techniques such as data mining techniques, time series analysis etc. Different approaches implemented by the researchers are as shown in Fig 4.

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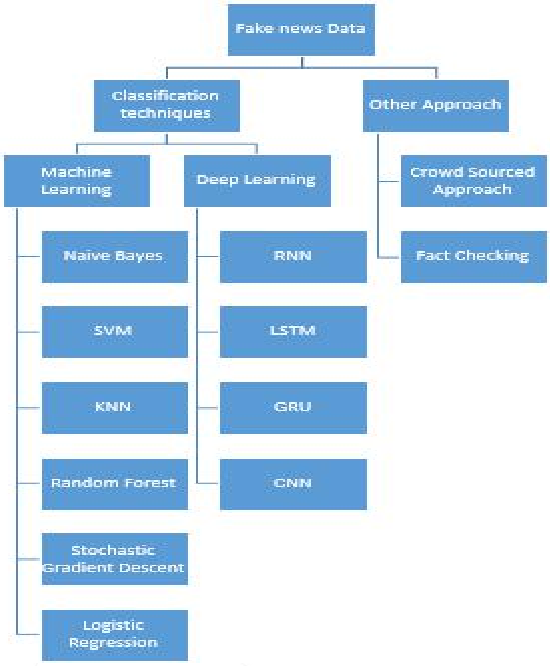

Figure 4. Various approaches used for fake news detection

Classification Techniques

Articulating the fake news detection as a classification problem is a ubiquitous strategy that has been taken into consideration by the researchers.

Machine learning techniques

Machine learning algorithms have been attested to be downright useful for the classification tasks. Majority of the machine learning techniques that have been used in this field have employed supervised learning.

Support Vector Machine (SVM) is one of the supervised algorithm that is used for the classification task and is also preferr ed for the fake news detection tasks. According to an experiment done in order to analyze the various classifiers that has been used for fake news detection, SVM outperformed other classifiers and had the best F1 score [48]. Similarly, while analyzing t he effectiveness of various classifiers using various text models, like Term Frequency- Inverse Document Frequency (TF-ID F), Count Vectorizer (CV) and Hashing Vectorizer (HV), Linear Support Vector Classifier (SVC) with the accuracy of 93.2% outperformed other models [49].

Content based feature has been majorly exploited in most of the SVM based approaches. While differentiating the news on the basis of linguistic difference an accuracy of 78% was obtained by using linear SVC [50]. Similarly, an F1 score of 0.84 a nd 0.95 was achieved by SVM on two different data sets when text features and linguistic cue features were used to conduct d eception detection [51]. SVM based algorithm to identify satire news pieces in order to minimize deception detection precisel y detects satirical news with precision of 90% [52]. Improved linguistic feature set with word embedding along with ensemble algorithm and SVM with linear kernel baseline classifier classified fake news with an accuracy of 95% [53]. Among the vari ous classification approach used to create a text processing model for the automatic identification of fake news, SVM gave the best prediction with an accuracy of 87% [54]. To explore the motive of fake news, the authors proposed a set of features, na mely, stylistic, complexity and psychological features and suggested that the content of fake and real news are a distinguishin g factor in addition to title being a strong differentiating factor between the news [20]. Linear kernel SVM achieved an accura cy of 77% by using the features for body and text. To substantiate the article content and title, various machine learning mode ls were deployed, out of which SVM outperformed the models with an accuracy of 91.6% [55].

Apart from SVM, another widely used algorithm is Random Forest Classifier. Random Forest is composed of many decisio n trees and because of parallel computing it is easy to generalize [56]. Various experiments show that, the effectiveness of Ra ndom Forest Classifier with respect to other classifiers. The authors analyzed the hashtags that were used in twitter during the Hong Kong protest to evaluate the fake news using various classifier among which, the random forest classifier gave an accur acy of 92.4% [11]. Similarly, when only the text feature was used, Random Forest gave an accuracy of 95% to detect the fake news in three different languages regardless of the source of the news [57]. When the performance of different classifiers was compared using the bag of words approach, Random Forest had the best F1 score of 0.702 [58].

A method to automatically detect fake news on Twitter using two Twitter datasets, CREDBANK and PHEME employed R andom Forest to assess the credibility of the news [41]. The classifier achieved an accuracy of 66.93% in PHEME dataset and 70.28% on CREDBANK dataset. Random Forest Classifier was implemented to classify the rumors by exploiting the tempora l and user features [59]. It achieved an accuracy of 84.61%.

Another widely used algorithm is the logistic regression Logistic regression along with four other classifiers were trained to detect the fake news and their performance were evaluated [48]. Logistic regression comparatively gave a better F1 score of 60%. The application of machine learning techniques in the field of fake news detection were explored and it was found that a mongst the various classifiers, logistic regression had an accuracy of 98.25% [60]. Likewise, logistic regression was used for t he stance detection of headlines with regard to the body of the article especially for clickbait detection [61]. For the related ne ws label, logistic regression achieved an accuracy of 93.64%. Logistic regression along with Boolean Label Crowdsourcing

(BLC) achieved high accuracy when, the Facebook posts were compartmentalized as hoax and non-hoaxes based on the users who liked the post [62]. A ML based method for combining news content along with social context feature was proposed for fake news detection [63]. Logistic regression was used for social signal. The model obtained an accuracy of 81.7% when it was implemented within a Facebook messenger chatbot and validated against real world application.

Naïve Bayes algorithm gives the best result even with limited amount of data and is also widely used for detection of fake news. Various model that has been proposed using Naïve Bayes algorithm gives considerably good result. The content and the title of the article were analyzed in order to verify the article, the performance of various machine learning classifiers were evaluated and Multinomial Naïve Bayes outperformed other classifiers with an accuracy of 92.06% [55]. Similarly, when Naïve Bayes along with various deep learning techniques was used to identify and classify news articles, it performed considerably well with an accuracy of 90% [64]. Naïve Bayes was employed to classify fake news and it gave an accuracy of 74% [65]. Similarly, Multinomial Naïve Bayes algorithm, was used to build a model to detect fake news, the model had an accuracy of 88% [66]. The model could perform better, had SVM been used instead of Multinomial Naïve Bayes.

Approaches based on stochastic gradient have also been adopted to detect the fake news. The performance of different training models was evaluated, amongst which stochastic gradient, when trained on a single dataset had an accuracy of 77.2% [67]. Similarly, stochastic gradient descent has been used by researchers for the comparative analysis of classifiers used to detect fake news [10], [48], [68], [49]. Apart from Stochastic gradient, K-nearest neighbor has also been used for fake news detection, though it did not give better performance [68].

An approach based on ensemble learning has also been implemented for the detection of fake [68]. An accuracy of 95.49% was achieved when ensemble method along with the stylometric and text feature was used.

A hybrid framework for detecting fake news which reuses machine learning model for the task of classification of news was proposed [69]. The model uses NLP features along with knowledge verification feature and sentiment analysis.

Deep learning techniques

Lately, deep learning has been widely implemented for classification. The computational capability of deep learning algorithms is better than that of machine learning algorithms. Unlike the machine learning models, deep learning models extract the hidden features and representations in text, images and tweets for detecting fake news [4]. The most widely used models for this purpose are Convolutional Neural Network (CNN), Recurrent Neural Network (RNN). CNN and RNN can identify the complicated pattern in a textual data [41].

Recurrent Neural Network (RNN) are a class of neural network which is able to handle sequence of any length and attain long term dependency [70]. RNN was used to attain the temporal pattern of user activity of a given article in a model, which combined the text of the article, the user response towards the article and source used to promote the news [71]. The model was used to automate the prediction of fake news and achieved an accuracy of 89.2% on Twitter dataset and 95.3% on weibo dataset. Similarly, RNN has been adopted in a distributed architecture to tackle fake news [72]. The model achieved an accuracy of 93%. When the sequence becomes longer, the old memory of RNN will fade, hence Gated Recurrent Unit (GRU) and Long Short Term Memory (LSTM) is designed to have more persistent memory [73]. Since, most of the work in the field of fake news detection, concentrates on the content and the social context, emotion based fake news detection framework was proposed [74]. In the proposed framework, RNN is used to learn the basic textual features, whereas, GRU is used to capture the contextual feature and model the emotional feature representation of the words. The framework achieved an accuracy of 87.2%.

Authors have put forward an ensemble learning approach in order to automate the detection of fake news in the online portal and assay the context of short sentences and news in order to provide a credibility score 75. Amongst the various classifiers used, LSTM obtained the best result with an accuracy of 97%. A pre trained probabilistic LSTM has been employed to detect the credibility of messages spread through WhatsApp [76]. The pre trained probabilistic model is used to classify a message as a claim or an opinion. Similarly, Natural Language Processing (NLP) is leveraged to consider the contextual similarity between the claim and the article. The model obtained an accuracy of 78.09%. A bi-directional LSTM recurrent neural network based model to detect the fake news have been proposed [42]. The model has been sampled on two datasets obtaining an accuracy of 91.08% and 98.75% respectively. Hybrid deep learning model of LSTM and CNN is used for identification of the features of the twitter posts and classify the fake news based on both text and image [77]. The model obtained an accuracy of 82%. Likewise, Authors combined CNN and LSTM to determine the accuracy of statements from multiple pieces of information [78]. The model obtained an accuracy of 38.81% on the LIAR dataset. Similarly, CNN and LSTM were combined to detect fake news, it obtained an accuracy of 97.3% [64]. When the authors combined, CNN and BI-LSTM they obtained an accuracy of 44.87% on the LIAR dataset. [45]. The combined model outperformed the performance of individual models. An early fake news detection method based on enhanced text representation was proposed by the researchers [79]. The method utilized CNN in order to capture the local order among the successive sentences and LSTM to attain the document representation. The method was implemented for four different datasets, two each for English and Chinese. The method obtained an accuracy of 88.42% and 93.78% for the English datasets and 81.74% and 90.34% for Chinese dataset.

A CNN based multimodal fake news detection model was proposed by the authors to identify the fake news stories. [80]. The model obtained an accuracy between 75% to 85% on Politifact and GossipCop fake news dataset. The model performs better when the linkage among textual and visual information is utilized. Two convolutional neural network are combined to assimilate metadata with text in order to detect fake news [81]. The model obtained an accuracy of 96% when text and author were given as the input. The enactment of fake news detection based on visual modality was improved by using CNN and bi-directional GRU [82]. The model obtained accuracy of 84.6% in twitter and weibo dataset. CNN outperformed all other models for detecting fake news while using LIAR dataset [44]. The model obtained an accuracy of 27% when CNN was used. Multilevel word feature based on CNN was used to identify fake news [83]. The model obtained an accuracy of 91.67%. The accuracy of existing fake news detection model was improved by using CNN [84]. The model obtained an accuracy of 98.36%.

Three level Hierarchical Attention Network (HAN) was employed for prompt and accurate detection of fake news [85]. The model obtained an accuracy of 96.77% by using headline as a distinguishing factor. Deep Neural Network obtained an accuracy of 98% when it was used for text analysis for detecting fake news [86]. Similarly, Deep Neural Network was used to enhance detection of fake news by combining both the news content and social [87]. The model achieved an accuracy of 85.86% and 88.64% with buzzfeed and Politifact dataset respectively. Convolution based graph neural network obtained an accuracy of 84.94% while detecting context based misinformation [88]. A Dense Neural Network architecture was proposed to provide a stance between headline and article body [89]. The accuracy of 94.21% was obtained by the model. Capsule Neural Network was used for detecting fake news and the model obtained an accuracy of 40.9% on LIAR dataset and 99.1% on ISOT dataset [90].

A deep learning based, discourse level analysis is used for the deception detection [91]. The model achieved an accuracy of 74.62%.

Other Approaches

Apart from the classification techniques, fact checking, crowdsourced approaches have been used to verify the news. Manu al fact checking can however not be the optimal solution to identify fake news since it consumes the time along with the effort. Several networking sites have utilized the crowdsourced approach to minimize the propagation of unverified news by leverag ing the user to flag a story as misinformation if the user feels so and if there are enough flags, the news is then considered as misinformation. An online algorithm CURB was put forward to leverage the crowd to detect and minimize the spread of misi nformation [92]. The CURB algorithm selects stories for fact checking based on flagging of the misinformation. The algorith m worked efficiently with the real world dataset of Twitter and Weibo and was able to control the misinformation before it be came viral. A robust model against spammers utilized the crowd sourced approach to minimize the spread of fake news [93]. The proposed algorithm 'DETECTIVE' performs Bayesian inference for detecting fake news by considering the user engage ment in the posts. This model leverages community signals for fake news detection.

A framework for evaluating the spread of misinformation in social networks has been proposed [94]. The method explores cognitive psychology to tackle the spread of misinformation and validated using twitter.

Rhetorical Structure Theory (RST) has been used as the analytical framework to distinguish among deluding and real storie s on the basis of their coherence and structure [96]. After the RST analysis Vector Space Model (VSM) is used to assess each story's position in multidimensional RST space concerning its distance from veracious and deceptive centers as a measure of t he story's level of deception and truthfulness. Similarity of 0.67 has been reported by the authors between the human assessm ent and the proposed method.

A multistage intervention framework to stop the spread of fake news in social networks by merging reinforcement learning with point process activity network model has been proposed [97]. The authors have formulated fake news mollification as th e problem of optimal point process in a network and the fake news mitigation problem is mapped to optimal policy problem i n a Markov Decision Problem (MDP) which is then solved by the model based least-square temporal difference learning speci fic to the content of point process.

Unsupervised strategy for the detection of fake news by making use of social media traces has been realized for developing GTUT, a graph based approach for discovering fake news [98]. The model utilizes graph based approach, such as biclique id entification, graph based feature vector spreading and label spreading. The model achieved an accuracy of 0.80 and 0.77 with politifact and GossipCop dataset respectively.

A Tri relationship embedding model, TriFN models the publisher news relation and user news interaction simultaneously f or fake news classification [99]. Experiments done to assess the definitiveness of the model, indicates that the model can achi eve good performance even in the early stage for fake news classification.

The problem of image manipulation for spreading fake news has been addressed by an algorithm which detects and localiz es image manipulation [100]. The authors have presented three variation of self-consistency model namely: Camera Classifica tion; XY- Consistency, which attests whether the patches are spatially consistent; Image-Consistency, that straightway forecas ts whether two patches are selected from the same image. The model obtained an accuracy of 98% in Columbia data set, 87% in Carvalho dataset and 55% in Realistic Tampering dataset. Similarly, pattern recognition solution was used for detection of f orged images [101]. By utilizing image processing for the detection of fake news the model obtained an approximate accuracy of 71.3%. Table 1 depicts the implementation detail of the algorithm along with the accuracy and the dataset details.

Table 1. Implementation Details of the Algorithm

Reference	Dataset Details	Algorithm	Experimental Setting and Accuracy
Singhania, Fernandez & Rao, 2017 [85]	65% from 2016 US election and politics, 15% from regional news, 15% from world news, 5% from entertainment.	Gated Recurrent Unit Bi-directional Recurrent Unit	Training: validation: testing in proportion of 20:10:70 Accuracy: 96.77%
Buntain & Golbeck, 2017 [41]	PHEME and CREDBANK	Random Forest Classifier	Restricting each source dataset to its most performant character subset and training a 100 tree random forest classifier. Accuracy: 66.93% on PHEME and 70.28% on CREDBANK.
Granik & Mesyura,	Buzzfeed news. The dataset	Naive Bayes classifier	Accuracy: 74%.

2017 [65]	contains information about facebook posts.		
Wang, 2017 [44]	LIAR	SVM, Logistic Regression, Bi-LSTM, CNN and Hybrid CNN	0.5 and 0.8 as dropout probabilities and 5 training epoch. Accuracy: 27%.
Dyson & Golab, 2017 [67]	Dataset published by signal media	Decision Tree algorithm, Random Forest Algorithm, SVM, Gradient Boosting algorithm, Logistic regression algorithm.	90% data is used for training and 10% data is used for testing. Accuracy: 77.2%
Helmsletter, Paulheim, 2018 [40].	Twitter API, DMOZ catalog, tweets from politifact.	Naive Bayes Algorithm, SVM, Decision Tree, Neural Network, Random Forest, XGBoost.	Cross Validation on noisy training data, Train the model on training set and validate them against a manually created gold standard. Accuracy: 90%.
Roy, Basak, Ekbal & Bhattacharya, 2018 [45]	LIAR	CNN, Bi-LSTM	Accuracy: 44.87%
Huh, Liu, Owens & Efros, 2018 [100]	Carvalho, Columbia, Realistic Tampering	EXIF	2-layer multilayer perceptron for computing patch consistency on top of EXIP consistency model prediction was trained for 10,000 iterations. Accuracy: 98% in Columbia data set, 87% in Carvalho dataset and 55% in Realistic Tampering dataset
Della Vedova, Tacchini, Moret, Ballarin, DiPierro & deAlfaro, 2018 [63]	FakeNewsNet Data from facebook post retrieved using facebook graph API	Logistic regression, Harmonic Boolean label on crowd sourcing	Shuffle split cross validation with 50 iteration and training set 0.1. Accuracy: 81.7%.
Choras, Gielczyk, Demestichas, Puchalski & Kozik, 2018 [101]	Images from CASIA database	FLANN and SURF	Accuracy: 71.3%
Kaliyar, 2018 [64]	Dataset from Kaggle	CNN, LSTM, Naïve Bayes, Decision tree	CNN accuracy: 98.3% CNN+LSTM accuracy: 97.3% Naïve Bayes accuracy: 90% Decision tree accuracy: 73%
Karimi, Roy, Saba-sadiya & Tang, 2018. [78]	LIAR	CNN, LSTM	80% of the data is used for training, 10% for testing and 10% is used as development set. Accuracy: 38.81%.
Ozbay & Alatas, 2019 [10]	Buzzfeed, Random Political News Dataset and ISOT dataset.	23 supervised artificial algorithms including Bayes Net, Stochastic Gradient Descent, J48, Bagging, Decision Tree, etc.	70% data is used for training and 30% is used for testing. Accuracy of 65.5% for Buzzfeed dataset, 68% for Random Political News Dataset and 96.8% for ISOT dataset.
Agarwal, Sultana, Malhotra & Sarkar, 2019 [48]	LIAR dataset	Naive Bayes, SVM, Logistic regression, Stochastic Gradient and Random Forest classifier	LIAR dataset has its own training, testing and validation dataset hence data splitting was not done. F1 score of 61%.
Shu, Wang & Liu, 2019 [99]	FakeNewsNet	Logistic Regression, Naive Bayes, Gradient Boosting, Adaboost, Decision tree, Random forest, XGBoost	Cross validation strategy. Accuracy: 86.4% for buzzfeed and 87.8% for politifact.
Benamira, Devillers, Lesot, Ray, Saadi & Malliaros, 2019 [88]	Buzzfeed election data set, Burfoot and Baldwin Dataset	Graph Convolutional Neural Network, Attention Graph Neural Network.	4 layers, 4 neighbors and 6 hidden unit and learning rate of 0.01. and for training 1000 epoch. Accuracy: 84.94% for 20% labeled data.
Amine, Drif & Giordaro, 2019. [81]	Dataset from Kaggle	Convolution Neural Network	90% data is used for training and 10% data is used for testing and

			for hybrid model 50 training epoch is used. Accuracy: 96%
Bahad, Saxena & Kamal, 2019 [42]	Dataset from Kaggle	Bi-directional LSTM	60% of data is used for training, 20% is used for testing and 20% is used for validation. Accuracy:91.08%
Zervopoulous, Alvanov, Bezas, Papamichail, Maragoudakis & Kermanidis, 2020. [11]	Fake news data set- Retrieval from twitter Election Integrity Hub. Real News data set- Tweets from the accounts of news agencies are retrieved.	Naïve Bayes, Support Vector Machine, Random Forest.	5-fold cross validation. Accuracy: 92.4%.
Kula, Choras, Kozvik, Ksieniewiaz & Woznaik, 2020. [86]	ISOT Fake news dataset and Getting real about fake news.	Deep Neural Network	80% data for training, 10% data for validation and 10% for testing. Accuracy:98%.
Zhou, Wu & Zafarani, 2020. [80]	Politifact and GossipCop	Convolutional Neural Network	80% data is used for training and 205 data is used for testing. Accuracy: 87.4% for politifact and 83.8% for GossipCop.
Reddy, Raj, Gala & Basava, 2020. [68]	FakeNewsNet and McIntire Fake News Dataset	Random Forest, Naive Bayes, KNN, SVM, Logistic Regression, Boosting with Adaboost and Stochastic Gradient Boosting, Bagging with General Bagging classifier and extra Tree Classifier	The training set has a balanced distribution of 49.9% of real news and 50.1% of fake news. Accuracy: 95.49%.
Agarwal & Dixit, 2020 [75]	LIAR dataset and Fake news dataset from Kaggle.	Naive Bayes, SVM, Convolution Neural Network, Long Short Term Memory	Accuracy: 97%.
Gangireddy, Padmanabhan, Long & Chakraborty, 2020 [98]	GossipCop and Politifact	Bi-Cliques	Accuracy: 80% for politifact and 77% for GossipCop.
Uppal, Sachdeva & Sharma, 2020. [91]	Kaggle, Buzzfeed, politifact	Gated recurrent unit	300 steps with mini batch size of 50 docs, initial learning rate of 0.01 and L2 regularization set to 0.01. Accuracy: 74.62%.

VI. Future Scope and Conclusion

The implications discussed in the paper are applicable to the real world scenario. Fake news detection is relatively a new field in the area of research although a plethora of work has been done. The state of art review has shown that the work done in this field are flourishing and the outcomes attained from the research and the experiments are promising. However, there are plenty of works which can be improved or implemented in this field.

Most of the work done in this field focuses on supervised learning models. Hence, unsupervised learning model can be developed for detecting fake news from the unlabeled data in the web. Lack of publicly available large scale dataset results into lack of benchmark for comparison amongst various algorithms. Similarly, there is dearth of dataset which includes videos and images. Hence, a multimodal dataset that covers all kinds of fake news should be available. Real time dataset is a major concern for fake news detection. Deployment of application which aide in real time detection of fake news is a necessity. Similarly, the verification of the source of news has not been focused on. Hence, a fake news detection method based on the verification of the news source can be proposed. Likewise, most of the work done in this field focuses on a single language and only handful of work has been done in detection of fake news in multiple language. Early detection of fake news is still a challenge for most of the researchers, since early detection requires real time learning of the news. Hence, detecting fake news at early stages before it spread is a challenge. Cross platform detection of fake news is a major issue for the researchers. As people have accounts in various other social media platforms, the news can easily propagate from one platform to another. Most of the work focuses only on a single platform. Hence, it is necessary to develop a cross platform fake news detection model.

This work may aid the researchers to understand the different types of fake news and the impact of fake news from both social and technical perspectives.

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