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Exploring the Insights on Fake News Detection on Social Media

R. Sandrilla¹, Dr. M. Savitha Devi²

¹Research Scholar, Department of Computer Science, Sacred Heart College (Autonomous), Tirupattur, Vellore Dt India

²Department of Computer Science, Periyar Constitution College of Arts and Science, Harur, Dharmapuri Dt. India

Abstract: *The advent of Web 2.0 technologies and the social media enables the users to express their opinions and experiences over the Internet. Due to the exponential growth of media rich information on social Media and other modern networks spreading of fake news plays a crucial part. Despite of this, detecting the fake news from the true ones is becoming impossible. Thus, this leads to the problem of deciphering False news. This research aims to provide a glimpse of knowledge on modern diaspora of the fake news in social media. Subsequently this paper includes a discussion on existing fake news detection and Classification based on Linguistic cue and Network analysis approaches. Finally, we conclude the paper with open research challenges and techniques in-order to guide for the future research endeavor.*

Keywords: *Classification, Fake News detection, Social Media, Fact Checking*

I. INTRODUCTION

This document is a template. For questions on paper guidelines, please contact us via e-mail. With the explosive growth of a vast amount of textual content in the Web 2.0 applications, news portals, and social networks, there is a huge need of analyzing and extracting the knowledge from the posted textual content due to the richness of opinions and attitudes in the user-generated content [1]. Social media sites and online social networks are a double-edged sword, especially for news consumption. Social media offers a low cost, rapid dissemination of information, and easy access to the users to consume news from social media. Despite, it enables the widespread of false information termed as ‘fake news’ which remarkably tends to create the negative impacts on the individuals and society. Hence, detecting the fake news on social media has become an emerging research topic in recent years [2]. Online social networks such as Facebook and Twitter have often faced scrutiny for being unable to curb the spread of fake news. Nowadays, social media sites have been increasingly used as the most fascinated tools for discovering the real-time knowledge pertaining to emerging threats, social events, product trends, and epidemics. In the online social networks, there are numerous motivations behind the widespread of fake news that include harming the reputation of the business, making political gains, seeking attention, and increasing advertising revenue.

Fake news detection has become a central research topic in the news industry due to the need of assessing the veracity of digital content over the constant spread of false information [3]. The main aim of the sensationalism of inaccurate eye-catching and intriguing headlines is to retain the attention of audiences throughout all kinds of information broadcast [4]. In the social networking sites, the reach and effects of information spread are significantly grown at a fast pace in which false information has attracted a tremendous potential to cause real impacts within minutes over the millions of users. To understand the public attitude towards various events, entities, and products, it is necessary to recognize the polarity of the opinions of the users of the social network [5]. In the social media sites, analyzing the user comments from a topic-centric perspective provide significant information about public stance, attitude, and feelings towards a specific event.

The conventional researchers have applied the sentiment and opinion models to recognize the opinion of a particular entity or an event [6]. Several former research works have focused on determining the fake news from the real facts in the user-generated chat information by exploiting the machine learning algorithms [7].

The social network sites have crowd-sourced solutions to resolve the fake news identification problem, include separating ‘shares’ from personal information, exploiting verified news sites, Snopes partnership, headline, as well as content analysis, and time delays on ‘reshares.’

The great challenge to the researchers is to develop a tool that which help the avid readers to decipher what they are inspecting is false or real. we have is, how do we as researchers produce. Subsequently to bring out with the best result it is necessary to explore an anticipatory study on the techniques for learning purposes. In the rest of this paper, we cover numerous facets of investigation problem of fake news detection. In Section II, we describe the potential applications and multiple platforms that is castoff to disseminate the news content effectively and extensively. Next, Section III discusses the types of data a news article can contain and

what is the impact of each type of data to readers, and then Section IV provides an understanding of different categories of fake news. Following that, in Section V, we present an overview of existing fake news detection methods and compare them from different perspectives. Further, Section VI describes the existing data sets. In the online social networks, fake news detection becomes an emerging research area in a data mining perspective. Social context based fake news detection are available for fake news detection researchers. Finally, in Section VII, we conclude the paper by highlighting open research challenges in the area of fake news detection.

A. Potential Applications

Model plays a crucial role in the rumor detection using social media. Fake news detection has been used in a myriad of application areas such as to improve the trust of social media sites and increase the dissemination of real news rather than the fake news among the people. With the rapid increase of fake news spread, the fake news detection models assist in reducing the widespread of misinformation over the social media sites. For instance, in France, the fake news was overflowed through the social media before the 2017 presidential election. To deal with spreading of such fake news, the fake news detection methodology plays a crucial role in the social network.

II. NEWS PROVIDER PLATFORMS

Though there are many social media which provides the real information, developing and spreading of fake news is a malicious act. There are people who voluntarily develop a fake news to become popular.

The three very common types of fake news providers are socbots, standalone websites, and cybernetic organisms. In 2017, two-thirds of U.S. adults get news from social media, that is 5% jump from 2016 numbers [8].

In this section we dive deep into analysing the list of platforms where the news contributors and the underlying source of news is broken down into categories.

- 1) *Trolls*: Trolls are the great giant's, where the real humans play an active role in spreading of the fake news, sometimes to disrupt the online communities. For instance, there has been evidence that claims nearly "1,000 Russian trolls were paid to spread fake news on Hilary Clinton," which discloses how actual people are performing information handling in order to change the views of others [9]. The main goal of trolling is to resurface any negative feelings harvested in social media users, such as fear and even anger, so that users will develop strong emotions of doubt and distrust [9]. These are created with a standalone website where they can have a detected URL which is used in creating a social media post
- 2) *Widespread Live News Page*: These sites deliberately publish the fake news. False news is often spread with fake news sites. It is like the customized standalone website.
 - a) *Read Blogs*: Blog are another personalized website which are created directly by the individual user
 - b) *Media Websites*: This is the place where one can share text information, upload photos, videos and audio to the websites that can be easily accessed from any part, anytime in the world. Embedding is also allowed in this type of websites.
- 3) *Socbots*: It is an unethical socialbots which in turn controls the social media account. These are the bots which steal the data or just done for time pass to make the real user to reshare and spread the fake news.
 - a) *Facebook*: Facebook are merely a news source where it allows the users to post the content as they wish. It cannot be a news source which is more reliable and unreliable
 - b) *Twitter*: Twitter is a platform where it carries a steady stream of tweets. This has been hailed as a good news source. Twitter can be either with enormous amount of reliable site and invaluable source of valuable information.
- 4) *Cybernetic Organisms*: This is a compound word commonly known as cyborg, along with the human users they use automated software to spread the fake news. These kinds of organ and biomechatronic body supports the human users to create the unintentional fake news.
 - a) *E-mails*: where electronically messages are distributed from one place to another with one or multiple recipients through the internet.
 - b) *Podcasts*: A podcast is a discontinuous sequence of digital multimedia files which a user can easily accessed through the internet by the user.
 - c) *Live Radio Services*: It is a real time audio broadcaster.

Thus, the way in which we consume news earlier is totally changed and the users increasingly getting their news through social media sites

III. TYPE AND FORMATS OF DATASETS

This section relates to the types and formats of news consumed online. There are four major format types available in which the users consume the news. Few are very popular among the online news.

- 1) *Audio-visual aid*: This is an integration of various forms of media aids which is commonly known as multimedia. These Multimedia includes formats include images, video, audio, and graphical form which easily seek the consumers attention towards it.
- 2) *Context*: This is a form of textual/ word-based linguistics which mainly focusses on context. More than words and a sentence it makes a semantic characteristics' such as definite tone, and grammar.
- 3) *Embedded content*: Here the embedded contents are related to the hyperlinks available online which makes various formats such as living Content, Interactive Content and Stories. Normally hyperlinks make link with different sources and increases readers belief by proving the hypothesis of the news story.
- 4) *Audio*: It is a part of multimedia which is earlier discussed as audio visual aid. This acts as a standalone medium for the consumption of news from the source. The Various audio type datasets are, pod casts, broadcast network and radio services.

IV. CATEGORIES OF FAKE NEWS

There are four broad categories of fake news, according to media professor Melissa Zimdars of Merrimack College. [10] Apart from that there are five forms which are collectively referred to as false news. We summarize this categorization.

- 1) *Category I*: Satire/comedy sites which has a potential to be shared as actual/literal news.
- 2) *Category II*: Fake, false or regularly misleading news- that is some sort of true but used in wrong context. This type of news depends on outrage by using distorted headline and decontextualized information in order to gain profits, shares and likes as such.
- 3) *Category III*: Sloppy report that fits an agenda. This news contains some grains of truth that are not fully verified and that support certain position or view.
- 4) *Category IV*: Websites that may circulate misleading and/or potentially unreliable information where there is no established baseline for truth.
- 5) *Category V*: Intentionally Deceptive news sometimes use clickbait which is fabricated deliberately to make money or to create confusion or discontent

The researchers have studied fake news from diverse perceptions and provided a wide-ranging categorization representing different types of fake news, e.g. by Rubin et al. in their recent paper [11]. The above categories of news are manipulated in some way and distributed through few channels which are potted below.

- a) *Visual-Based*: Combination of merged, cropped images, video visuals are some type of fake news which represents the content in graphical or diagrammatical depiction [12].
- b) *User-Based*: It is a customized fake account targeted towards the audience representing the basic requirement such as to specify which age community, gender and culture.
- c) *Post-Based*: Post-based fake news is mainly concentrated to be appeared on social media platforms. Post can be a Facebook post along with image or video and caption, a tweet, meme, etc.
- d) *Network-Based*: Network-based news are oriented towards certain members of an organization that are connected in one way or the other, this ideology is also applied to group of friends on Facebook and group of mutually connected individuals on LinkedIn.
- e) *Knowledge-Based*: Knowledge-based fake news contains scientific or reasonable explanation to an unresolved issue, these type of news stories are designed to spread false information, e.g. false article on how to cure asthma.
- f) *Style-Based*: Focuses on the way of presenting to its readers, fake news is written by majority of people who are not journalists - the style of writing can be different.
- g) *Stance-Based*: Stance-based type in-lines with above mentioned style-based type, stance is different in a sense that it focuses on how statements are being made in an article. Truthful news articles are written in a way to give sufficient information about the subject matter and it is on readers to take way the meaning of the story. Stance-based stories are written to provide very little information about the subject matter and to make a lot of statements (fake arguments).

V. LITERATURE SURVEY

Recently, the spread of fake news through social media is exclusively increased. This literature briefly reviews the social media messages classification approaches and fake news detection approaches.

A. Social Media Messages Classification Approaches

In the field of social media, sentiment analysis has received increasing attention among the natural language processing researchers. Fake news detection mainly focuses on classifying the social media messages, which is a fundamental problem in social data mining. In the social network, accurately categorizing the social media content enforces the precise filtering of information, which also assists to alleviate the information overloading. Recently, the social media platforms often meet the attacks of disinformation launched by malicious users. Several research works have focused on both the social media content and network information to find the malicious users such as spammers [13,14] and crowd surfers [15]. From the adaptive spammer detection research [13], it is assumed that if similar users spread the information, there is the existence of sharing similar properties. Accordingly, the consideration of network information for spammer detection belongs to only around the user instead of the corresponding information itself.

Classification algorithms are inappropriate for microtext in the social network owing to the characteristics of higher noise and lower dimension of social media text data. To improve information filtering, short text classification approach [16] presents 8F features and primarily captures the information about authors and reply-to users. The Enhanced Messaging for the Emergency Response SEctor (EMERSE) system [17] classifies and aggregates the tweets and text messages concerning the Haiti earthquake disaster. By exploiting the combination of 4 feature set such as uni-grams, uni-grams with Relief feature selection, abstraction, and topic words. In recent years, the ensemble classification approaches have attracted much attention of the research community for various types of textual data [18]. Tweet sentiment analysis model [19] exploits the ensemble classifier that consists of several base machine learning classifiers such as random forest, multinomial Naive Bayes, support vector machines, and logistic regression. It reports that the ensemble classifier improves the classification accuracy and compares the tweet representational strategies such as bag-of-words and feature hashing. Ensemble-based sentiment classification [20] employs an ensemble schema that combines three base learners such as Naive Bayes, support vector machine, and maximum entropy. In consequence, it recognizes the polarity of positive or negative in text data. From the results of sentiment classification approach [21], the ensemble classifier substantially improves the performance of individual base learners. This sentiment classification model employs five base learners, including Naive Bayes, decision tree, maximum entropy, support vector machine, and k-nearest neighbour, which are combined with a random subspace method. To recognize the emotions in the text, an approach [22] utilizes an ensemble classifier involving the combination of machine learning methods and knowledge-based methods. It has proved that the ensemble learning methods are a very viable model for sentiment classification.

B. Fake News Detection Approaches

Several research works have focused on rumor detection and information credibility evaluation to resolve the problem of detecting fake news. These methods are based on the predictive models to classify the fake news from the real news. Fake news detection methods are categorized into four major levels, such as (i) news content feature based detection using natural language processing techniques [23, 24, 25, 26], (ii) by applying the learning models of trustworthiness and source reliability [27, 28, 29], (iii) using network structure pertaining to the propagated news [30], and (iv) using the combination of linguistic, source, and network structure based fake news detection model [31, 32, 33, 34].

TweetCred [23] is a semi-supervised ranking model, which assesses the real-time credibility of Twitter content. It assigns a credibility score to tweets generated by users in a timeline, which is available as a browser plug-in. Linguistic model [24] classifies 130 thousand news posts and predicts four sub-types of suspicious news such as hoaxes, satire, propaganda, and click bait by building the predictive models. It employs the neural network along with the syntax and grammar features and the social network interactions to outperform the lexical models and to detect the deception. By utilizing sequential class rules, the learning model [25] identifies the ambiguous and misleading headlines based on the structure information. An approach develops a detection technique [26] based on searching for the enquiry phrases, clustering identical posts together, and collecting related posts which exclude these simple phrases in social media. Consequently, it ranks the clusters based on their likelihood of comprising a disputed factual claim. An incremental truth discovery framework [27] dynamically updates the object truth and source weight for the new arrival of data by analyzing the temporal relations among both the object truth and source reliability. To determine the users who spread propaganda from other neutral users on Twitter, the research work [28] explores four features by developing behavioural based

propaganda detection technique. The four features include high volumes of tweets sent by the users over a short period, retweeting even when publishing little original content, quick retweeting, and colluding with other. A temporal point process modelling framework [29] links the temporal traces to unbiased, interpretable, and robust notions of source trustworthiness and information reliability. It learns the parameters from the historical traces by developing an efficient convex optimization procedure. Computational fact checking method [30] enhances the ability to evaluate the veracity of dubious information, which approximates the complexities of human fact checking based on the shortest path between concept nodes with the consideration of semantic proximity metrics on knowledge graphs. Statistical analysis-based rumor detection approach [33] identifies that structural and temporal features distinguish rumor from non-rumor over time and tracks the precise changes to rumor features. Network Information Credibility Evaluation (NICE) platform [34] presents the algorithm that learns dynamic representations for social media information based on dynamic information, user information, behaviour information, and comment information. It classifies the social media information into rumours and non-rumours by applying an ordinary logistic regression model.

VI. DATA SETS

There are numerous online repositories that curate datasets. The following are popular data-sets that have been used for fake news detection:

- 1) *Buzz Feed News [35]*: Buzz Feed News is a collection information published in Facebook with title and links to an actual story or a post that is considered fake news. This data-set is useful for testing Linguistic methods, however, multimedia content is not part of this data-set, therefore certain analysis is not possible on text-only data-set.
- 2) *LIAR [36]*: LIAR is a bench-marking framework made available by University of California, Santa Barbara researchers. This data-set is also linguistic-based dataset and only contains text only data and has similar limitations like BuzzFeedNews data-set.
- 3) *PHEME [37]*: This data-set includes rumor tweets, collected and annotated within the journalism use case of the project [19]. It contains Twitter conversations which are initiated by a rumor tweet. Also, it is linguistic based data-set. It contains about 330 conversations (297 in English and 33 Germany).
- 4) *Credbank [38]*: The only data-set has contained social media data and allows users to perform analysis on Twitter data. This data-set signs off on all the categories except the visual data. It misses out on having multimedia data, but still makes it a very compelling choice for researchers who are also focused on fake news detection on social media.
- 5) *Newsnet*: A data repository with news content, social context and dynamic information for studying fake news on social media.

VII. FALSE NEWS DETECTION METHODS

There are various false news detection methods in which most of the methods are completely based on certain feature's selection methods and very few are model construction methods. In this section the popular fake news detection methods are discussed.

Deception Model based Methods- Deception is a deliberate act which misleads one which is fake. This is an act of trick intended to make somebody believing something that is not true. Data mining techniques are trivial and used in analysing the deception or unsuspected patterns in the text. the deceptive statements or claims from news content. The motivation of deception detection instigates from forensic psychology (i.e., Undeutsch Hypothesis) [39] and various forensic tools including Criteria-based Content Analysis [40] and Scientific-based Content Analysis [41] have been developed. The author states that detecting the deceptive and the real stories depends on theoretical approaches: Rhetorical Structure Theory (RST) and Vector Space Modelling (VSM) [42]. RST is a theory based on text generation. It is especially depicting the nature of coherence of text. VSM is model representing the all the news content or documents as vectors. This is used in content filtering the news from fake and real, providing the relevancy ranking to the document, retrieving the required information from the body of the news and used in indexing the text document. All the mentioned features can be easily done by analysing the results of the RST methods obtained.

A. Linguistic feature-based Method

Linguistic model is based on some feature's extraction Method. This Linguistic method completely works on document or text organization. It is categorised into various levels as words, Punctuation, Characters, Sentence, Forms. In-order to acquire the knowledge of fake news and real news in different aspect Common Linguistic Feature and Domain specific Linguistic Features are considered

- 1) *The Common Linguistic feature*: Are used often to represent numerous tasks in NLP. The distinctive common Linguistic features are under two categories mentioned below

- a) *Lexical Features*: Captures the word level and character level features such as from the whole word, lemmatized word, stemmed words, characters per word, frequency of word, and unique words
 - b) *Syntactic Features*: Is the techniques used to extract the features based on Context Free Grammar
 - i) *N-grams*- these are the most powerful techniques that is used to acquire the knowledge of both syntactic and semantic structure of a text. Unigrams and bigrams present in the text are captured using n gram technique. Normally the concept of n grams works by dividing the sentence into smaller sequences (Collection of words) considering m as the parameter that indicates the collection of sequences. If larger the m, the more context is captured.
 - ii) *Bags of words*- these are the simple algorithm used in natural language processing. Here it considers the sentence or a whole document which consists of bags of words. The concept of BOS works by considering the words and their frequency of occurrence in the sentence or the document disregarding semantic relationship in the sentences.
 - iii) *Punctuation* -Researchers on fake news detection (Rubin et al., 2016) and on opinion spam (Ott et al., 2011b) suggests that the use of punctuation can help the fake news detection algorithm to differentiate deceptive from truthful texts. We punctuation feature set consisting of twelve types of punctuation which is derived from the Linguistic Inquiry and Word Count software (LIWC, Version 1.3.1 2015) (Pennebaker et al., 2015). This includes punctuation characters such as periods, commas, dashes, question marks and exclamation marks.
 - iv) *Parts of Speech*- This is one of the psycho linguistic feature, where this feature can be effectively done by LIWC a powerful tool for the deception detection in various contexts. LIWC tool is used in extracting the collection of words that falls on the psycho linguistic features such positive emotion, perceptual process as well as parts of Speech. LIWC dictionary is a combined feature with a set of all LIWC categories. LIWC proves to be a valuable tool, it can cluster single LIWC categories into multiple feature sets: summary categories (e.g., analytical thinking, emotional tone), linguistic processes (e.g., function words, pronouns), and psychological processes (e.g., effective processes, social processes) [43].
- 2) *The Domain Specific Linguistic features*, which are specifically aligned to news domain, such as quoted words, external links, number of graphs, and the average length of graphs, etc.

B. Clustering Based Method

An unsupervised method for categorizing news articles based on their cluster membership Predictive Modelling Based Method.

C. Content Based Method

Any cues in order based on some informative content is primarily based on content-based method. In [44], [45] authors Chen, Bockzowski & Peer, explained Content Cues Method, this method is based on the ideology of what journalists like to write for users and what users like to read (choice gap). This content-based method can be either textual or Non-textual cues-based Method.

- 1) *Textual Cues based Method*: Since false news attempts to spread fake claims in news content textual method is a direct and straightforward method. Textual based method is covered completely by only text where the text presented tends to attract the users in-order to mislead them with false news. In [44], authors Chen, et al. explained Textual Cues Method, this method is based on the philosophy of what journalists like to transcribe for users and what users like to read which is also termed as choice gap between the user and the author. This method is approached in two different analysis
- a) *Semantic Analysis*: semantic analysis is a leverage level of analysis based on lexical analysers. The lexical analysis study about the individual words of idioms in various linguistic content. Semantic analysis helps in understanding the nature of the language, which plays an important role in convincing and attracting the user to believe the fake stories. The lexico-semantic uses lexical features to define the words with their meaning in the text. Semantic Analysis regulates the honesty of authors by depicting the degree of compatibility by their personal experience. [11]
- b) *Syntactic Analysis*: The syntactic analysis determines and describes the relevant components in the sentences grammatically. It breaks down the given news into its own constituents and states or labels the type of constituent it is and attracts the reader with its labelled headlines.
- 2) *Non-Textual cues Based Method*- Authors Chen, et al. [44] explained Non-Text Cues, this mainly focused on the non-text content of the news content. The non-Textual content is usually presented to a user has a text alternative that assists as a equal determination. Any information is message conveyed other than text need to be provided with informative non-text content as such, because the substitution should provide equivalent information. The various forms of non-textual content convey information to the users are images, captcha, multimedia files, graphical representations, animation images and Charts. The two different methods in analysing the text i) Use of an Image Analysis ii) User Behaviour analysis. The image is purely for

decoration and it mostly does not provide any information to the user whereas the alternative text appropriate to the image must be provided with a fewer words. The news reacts to a news story by looking the headlines of an image. So, multimedia plays a major role convincing a reader to make in believe in fake news or the subject matter in non-textual based method. if) Behaviour analysis judges about the user or the reader as how readers engage with news once they are attracted into the story. Understanding user behaviour and use of teasing images is the key to gain more traction on social media.

D. Propagation Based Method

The typical strategies that one can take to detect fake news based on propagation information. These studies can be classified into Cascade-based fake news detection techniques, which take direct advantage of news propagation path sand news cascades to identify fake news.

- 1) Network-based fake news detection methods, which construct a flexible network from cascades, using which fake news is indirectly predicted

VIII. EVALUATION METRICS

To evaluate the performance of the fake news detection algorithm, the experimental framework employs various evaluation metrics. The reviewed approach considers the fake news problem as a classification problem that predicts whether a posted social media message is fake or real.

Precision: It is the ratio between the number of accurately predicted fake news and the total number of predicted data that are annotated as fake news.

Recall: It is the ratio between the number of accurately predicted fake news and the total number of data that are annotated as the fake news.

F-measure: F-measure or F-score is the harmonic mean of the precision and recall.

$$F\text{-measure} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

Classification Accuracy: It is the ratio between the number of accurately predicted fake news and real news and the total number of evidences that are in the social media messages.

IX. CONCLUSION AND FUTURE SCOPE

In this review, the investigator realised that people surfing web have a blind opinion on posts published in social media. The serious action to be taken to detect the fake news from real ones. Reasoning out the problems and detecting the fake news in social media has become the emerging research topic today in the research area. So, the researcher explored the problems in false news by reviewing the existing literature in two different phases. In the social media messages Clustering approach, we introduced the precise filtering of information which helps to improve the information overloading, and in social media detection approaches we discussed on existing fake news detection methods and discussed on the types of fake news detection method successfully used to detect dishonesty type of Fake News Content Type. We also further discussed the datasets, and evaluation metrics.

We estimate that the subsequent are the crucial research challenges that can lead future research on fake news detection. Machine Learning and Data Science are modern-day fields of computer science which are indeed proficient to handle multifaceted problems and are attempting those problems is head on. These vast technologies mused be used to solve the problem of fake news on social platforms. Source of the news story has not been done in any existing methods, this calls for a new fake news detection method that can perform source verification and deliberates the source in evaluating fake news stories. This can be a promising future direction in fake news detection research and expand the field to other applications.

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