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Rumor Detection Using Machine Learning in Social Media: A Survey

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Abstract: ***The anonymous nature of social media plays a significant role in spreading rumors online. False rumors negatively affect communities and effective rumor detection techniques help in limiting such harm. Rumor detection has received substantial interest and several researchers have addressed rumor detection using various machine learning approaches namely classical machine learning and deep learning. This paper sheds light upon the current state of rumor detection in social media focusing on the techniques used as well as dataset.***

Keywords: rumor detection, machine learning, deep learning, social media

1. Introduction

Rumor is defined as one form of communication that do not confirm to the standards of truth, that affects personal and cultural context [1]. Another definition found in [2] is that rumors are unverified stories that circulate among people. Several factors contribute to the rumor spreading, a study in [3] found that people are more likely to transmit a rumor if it was delivered by a peer they know and they also found that people with anxiety repeat a rumor more than others. Another study in [4] found that people who share a common interest tend to distribute rumors and amplify them. Content plays a significant role in rumor spreading as researchers in [5][6] reported that certain contents are more likely to circulate than others, similarly,

In order to understand the rumor spreading process, researchers in [7] were the first to introduce a rumor spreading model that is inspired by the process of epidemic spreading and name it as the DK model. In the DK model, a population is divided into 3 disjoint groups: people who haven't heard the rumor yet (ignorant), people who have spread the rumors (spreaders) and those who stop the rumors (stiflers). Later, behavioral, and psychological researchers have built upon this model and derived equations that quantized the rumor spreading process [8] [9].

With the digital age, social media sites like Twitter and Instagram have emerged and become a valuable source of information, however, many issues arise like rumor and misleading information spreading [4]. Social media has worsened the issue, as everyone is able to pretend as someone else and post content without any form of verification [10]. One of the major examples about rumor spreading in social media was a rumor in Japan about the nuclear leakage caused by the Fukushima nuclear accident which caused panic among the Japanese community and led people to purchase large amount of salt [8]. Another example was about the Boston Marathon Bombing Event, where legal authorities requested information about possible suspects, however, this resulted in tremendous false information and rumors that distracted authorities. A political example was a rumor regarding the health of the US president Brack Obama, where the associated press (AP) accounts posted on Twitter that the president was injured due to an explosion in the White House. Consequently, the US stock market dropped significantly and reportedly 130 billion dollars were wiped out [4].

The automatic rumor detection filed is maturing with a wealth of well-defined and structured techniques and algorithms. First attempts to address this issue were based on feature engineering and classical machine learning approaches (based on features and training a classification model accordingly) [2]. The field has gradually broadened as deep learning has revolutionized the machine learning field [11]. Deep learning, widely considered to be a robust technique, has gained interest because it eliminates the need for manual feature engineering and made rumor detection a fully automated process [12] [13]. A whole range of different deep learning approaches have been introduces in the literature, such as those based on Convolutional Neural Networks (CNNs) [12] and Recurrent Networks (RNs) [13]. For this paper, it was of interest to investigate different approaches addressing rumor detection and highlighting their strengths and weaknesses as well as demonstrating any research gaps that would guide possible future research.

This paper is organized as follows: part 2 describes the publicly available dataset used in the field, part 3 represents the classical machine learning approaches, part 4 focuses on the deep learning approaches that constitutes a relatively new area. while part 5 concludes this paper and suggests possible future directions.

2. Dataset

Researchers recognized the need to create benchmark dataset that can be used to compare and experiment different rumor detection mechanisms.

1) PHEME Dataset
   Was introduced back in 2016 by Zubiaga et al [14]. The dataset is crawled from Twitter timeline using Twitter's API. The dataset has two classes rumor and non-rumor tweets captured during several major events [11]: Ottawa Shooting: which took place in Ottawa, Canada back in October of 2014. Charlie Hebdo Shooting: concerning the attack against a French newspaper called the Charlie Hebdo in January of 2015. Sydney Siege: which happened in the Lindt chocolate cafe, in Sydney, Australia in December of 2014. Ferguson Unrest: when residents of Ferguson, Michigan, USA, protested on August 9, 2014. Germanwings Plane Crash: the unfortunate event where a flight departed from Barcelona to Düsseldorf crashed in France. The dataset has been used extensively in the literature as it contains 5802 annotated tweets, 1972 of which are rumors, and the rest are non-rumor.
2) KAGGLE Dataset
   This dataset is publicly available through Kaggle's website in .csv format. It consists of three subfiles that contain texts from three different websites Snopes.com, Emergent.info, and Politifact.com. This dataset is advised for multiclass rumor detection problems as the classes are not binary; instead it has five classes: e true, false, mfalse (mostly false), mtrue (mostly true), mixture, or unverified [11].
3) Weibo Dataset
   This dataset consists of two sub dataset one collected from Twitter whilst the other is collected from Sina Weibo (weibo.com). Instead of manual annotation, authors used www. snopes.com, an online rumor debunking service to distinguish tweets containing rumors from the rest. For Weibo data, they extracted posts from the Sina community management center that contains previously known and reported rumors. The final dataset contains 2,313 rumors and 2,351 non-rumors [15].
4) COVID-19 Dataset
   Due to the vast volume of news emerging everyday during COVID-19, the need for a public COVID-19 dataset has arisen. This dataset was crawled from Twitter, using several COVID-19 tags so that only relevant tweets are considered. The dataset has several columns such as: the tweet, the class (rumor, non-rumor), the date of publication, sentiment, and stance [16].

3. Classical Machine Learning

Nowadays, Machine learning is so pervasive today that it probably can be used hundreds of times a day without knowing it. can be simply defined as a science that focus on how to program the computer to learn from data [2]. In recent years, machine learning-based techniques have been considered as promising viable approach for detecting rumors on social media. Many studies have formulated several machine learning mechanisms for dealing with the rumor detection problem social media platforms. These studies can be categorized into supervised, semi supervised, and unsupervised learnings. Most early studies as well as current work focus on applying the first and third approaches.

For the supervised approach, Yang et al. [17] conducted a study on enhancing the rumor detection in Sina Weibo, a widespread social media platform in Chania. This study introduced two new features in addition to the features in the previous studies [18], [19], and [20]. These two new features are client program used, and event location. The researchers conducted two experiments using a trained Support Vector Machine (SVM) classifier to compare the accuracy of it before and after including the new features. They reported that the average accuracy after adding the proposed features was (77%) which improved the previously proposed features average accuracy that was (72.5%). This has also been explored in a prior study on Twitter by Dayani et al. [21]. In this research, dataset in [19] has been expanded with more information about the tweets' owners. They applied K-Nearest Neighbor (KNN) on user-based features, and Naïve Bayes (NB) classifier on content-based features. The conducted experiments reported accuracy was (86%) for rumors endorsed, the same for rumors denied, and (74%) for rumors questioned. Another study applied on Sina Weibo by Wu et al. [22]. This study proposed a novel graph-kernel-based approach with an SVM classifier to prioritize propagation and sematic features for the rumor classification task. The authors applied graph-based SVM with Random walk kernel and RBF kernel. The experiment showed an accuracy equal to (91.3%). In addition, they concluded that their proposed algorithm suitable for early detection of rumors.

Over the last few years, some researchers have driven a further development of rumor detection in social media. Kim et al. [23] evaluated the use of some ensemble solutions by examining their unknown rumor detection performance compared with single machine learning models. They concluded that using content-based features only might be better than using all features to detect hidden rumors. Additionally, the paper proposed ensemble solutions (ESes) combining multi-ML models together to be applied symbiotically in rumors detection. In [24], Vinay et al. took a new direction in rumor detection enhancement. In this study, a new technique called "ConTheModel " for rumor detection ML models evaluation. This technique modifies the tweets by replacing the targeted words with their synonyms or antonyms. The aim of ConTheModel is to investigate the feasibility of confusing classifier-based detection methods to improve the models' performance. The approach has been evaluated by comparing the result of the original and the modified versions of ML models. In this study, Random Forest (RF), Multilayer Perceptron (MLP), Naive Bayes (NB), Support Vector Machine (SVM), and eXtreme Gradient Boosting (XGBoost) algorithm have been chosen for the evaluation. The research demonstrated that most of the ML models were confused in all three evaluation scenarios that had been conducted by showing a drop in the models' performance.

Semi supervised learning approach has been used rarely in detecting social media rumors. Alzanin and Azmi [25] proposed a system based on semi-supervised expectation–maximization to detect rumors in Arabic tweets. Further, they introduced two new features: tweet contains NSFW content and author followed by credible user. At the end of the study, the proposed system has been compared with supervised Gaussian Naïve Bayes (NB). The experiments results established that the accuracy of the proposed system achieved (80%) which is better than NB that achieved (78.6%). Another research has been done by Amutha and Kumar [26] which presented a model of dynamic rumor influence reduction with classification. In this model, semi supervised clustering algorithm (SSCA) and (Ising) model is employed to solve rumor propagation issue. To reduce the impact of the rumor from the dataset, Naïve Bayes, Random Forest and KNN were used. The experiment achieved high accuracy of KNN classifier (85.54%) compared with the other two classifiers.

Several studies suggested rumor detection models based on some unsupervised learning approaches. Raj and Meel [27] implemented a framework for unsupervised rumor detection that relies on the rumor post's content and social features using state-of-the-art clustering techniques. They used four types of clustering on PHEME dataset: RBF Spectral clustering, NN Spectral clustering, K-means clustering, Fuzzy C means clustering in their study. Compared with existing techniques, the proposed methodology demonstrates around 25-30% improvement in virous datasets. unsupervised learning has also been adopted in prior study by Kwon et al. [28]. They suggested a novel rumor classification algorithm that achieves competitive accuracy over different observation time windows. This study was conducted on real rumor cases extracted from Twitter's data. User and linguistic features gave better performance for short periods, while all the features resulted a good performance for long time. Chen et al. [29] studied rumor detection as an anomaly detection problem in Sina Weibo. The study conducted by applying actor analysis of mixed data on recent blogs of the suspected blogger. Their experiments resulted an F1 score = 81.33% for rumor detection, while for detecting non-rumor the F1 = 77.78%.

Table 1 presents a summarization of recent literature on rumor detection based on classical machine learning along with the best performance measures recorded in terms of accuracy (A), Precision (P), Recall (R) and F1 measure.

Table 1: Rumor Detection based on Classical Machine Learning Literature

Ref	Year	Algorithm	Dataset	Result			
				A	P	R	F1
[30]	2019	One Class Classification (OCC)	Zubiaga et al [31] and Kwon et al [28]	-	-	-	Z:0.74 K:0.93
[32]	2019	SVM, Decision Tree, Random Forest, K-Nearest Neighbour, Gradient Boost Decision Tree, Xgboost.	Weibo [15]	0.837	0.827	0.837	0.825
[27]	2021	RBF Spectral clustering, NN Spectral clustering, K-means clustering, Fuzzy C means clustering	PHEME [14]	-	0.976	0.485	0.649
[33]	2017	SVM, Conditional Random Field, Naive Bayes, Random Forest	PHEME [14]	-	0.667	0.556	0.607
[34]	2015	SVM, Logistic Regression, K-Star, and Random Forest.	MediaEval 2015	0.836	0.937	0.922	0.930
[35]	2015	Decision Tree, SVM, Random Forest	Castillo dataset	0.867	0.870	0.882	0.876
[36]	2020	Logistic Regression Classifier	Twitter	0.90	0.90	0.90	0.90
[37]	2015	Naive Bayes, Rule-based	Twitter	0.90	0.909	0.50	0.645
[38]	2013	Decision tree, SVM, Random forest	Twitter	0.897	0.923	0.883	0.878
[39]	2015	Logistic, Naïve Bayes, Random forest	News, Twitter	-	0.986	0.987	0.959

4. Deep Learning

Deep learning is one of the breakthrough technologies which took machines' understanding to a new level. It is a class of techniques that mimic human thinking and reasoning which emerges from studying the human brain visual cortex. Deep learning takes considerable time in training and this was a struggle back in the days of limited memories. However, recently, with the advancement of computational power and capacity, training deep leaning networks has become possible [40].

There exists a considerable body of literature on the use of Convolutional Neural Networks (CNNs) in rumor detection. A study in [12] not only adopted CNN but aimed at enhancing its performance by time series and sentiment features. In their model, they added s sentiment component in the form of SVM classifiers that determines the polarity of text. Another significant improvement is the attention mechanism that solves a common problem found with CNNs. Their experiments showed that the suggested model outperforms state of the art techniques on two public data sets. Similarly, authors in [41] adopted CNN but with a different perspective. They introduced a novel model that combines ensemble learning and CNN along with Nodes Proportion Allocation Mechanism (EGCN). In order to assess the applicability of such approach, they tested the model on a public benchmark dataset called the PHEME, which contains tweets collected during breaking news. Their work concluded that the graph inclusion in the detection process significantly improves the accuracy. Authors in [42] also explored CNN use and proposed a deep learning model based on a conventional neural network (CNN) to detect rumors spreading on Twitter. Due to the fact that CNN's performance is heavily dependent on several factors such as number of filters, windows size, and the number of units in the dense layer, they conducted several experiments with varying numbers to assess the best combination of values. For experiments they have tested using the PHEME dataset and concluded that their model outperform all the existing methods in terms of f -measures and achieved the best balance of recall and precision.

Another deep learning category employed by researchers is Recurrent Neural Networks (RNNs). One method employed by [43] proposed a novel deep recurrent neural network with a symmetrical network architecture. They also enhanced the data preprocessing phase by including posts posted by accounts having many followers and then incorporating sequential encoding for these posts. The tested their proposed model on the public Weibo dataset and concluded that the sequential encoding outperforms the term frequency-inverse document frequency (TF-IDF) or the doc2vec encoding schemes. Moreover, they highlighted that the inclusion of posts by accounts having many followers increases the accuracy. Furthermore, authors in [44], proposed a RNN based rumor detection model that address the propagation structure and generate more powerful representations. The model constructs two neural network trees a bottom-up and a top-down for rumor representation and classification. They tested the validity of the proposed approach using Twitter15 and Twitter16 dataset, and results showed that their model achieved superior accuracy of about 72% on these two dataset. RNNs have also been explored in prior studies by [45] where authors proposed a novel attention learning framework via deep visual perception based recurrent neural network (ViP-RNN) and a remarkable contribution of this work was that they combined CNNs and RNNs. They used RNNs to record the long-distance temporal dependencies of context information, while CNNs were used to capture low level lexical features. Their approach was tested on various real datasets and was proved to be effective

Long Short-Term Memory (LSTM) is a subcategory of RNNs that incorporates two types of nodes: cell states and hidden states which both play a role in controlling the information that travels in a neural network regulated by gates [46]. Research in [47] demonstrated the use of LSTM (bi-directional LSTM in particular) for false news detection. Their proposed model used Global Vectors for Word Representation (GloVe) and for the actual classification they provided three different options: CNNs, Vanilla RNNs and bi-directional LSTM. They investigated the performance of their model on two news dataset one labelled as FAKE or REAL and the other labelled as 1 for real and 0 for fake news. The result suggested that bi-directional LSTM performed the best in terms of training accuracy (99%), validation accuracy (89%) and testing accuracy (91%). Similarly, authors in [48] adopted Deep Bidirectional Gated Recurrent Unit (D-Bi-GRU) in the detection process with the focus on capturing the evolution of group responses over time. Information captured included emotional and semantic learned by D-Bi-GRU and their experiments yielded that the inclusion of such information improves rumor detection. Another work based on LSTM is found in [13] where authors defined an early rumor detection (ERD) model based on reinforcement learning and LSTM to learn the state sequence features. They tested the model on Twitter PHEME dataset and compare its performance against 8 other algorithms such as LSTM and LSTM-Attention. The result suggested that their model recorded state of art performance with 81% accuracy and 79% recall.

Table 2 presents a review of recent literature on rumor detection based on deep learning along with the best performance measures recorded in terms of accuracy (A), Precision (P), Recall (R) and F1 measure.

Table 2: Rumor Detection based on Deep Learning Literature

Ref	Year	Algorithm	Dataset	Result			
				A	P	R	F1
[49]	2021	CNN with optimized feature vector using filter wrapper technique.	PHEME [14]	-	0.776	0.745	0.732
[50]	2021	CNN with joint text and propagation structure representation learning.	Weibo [15] and Twitter	0.95	-	-	-
[51]	2021	CNN and LSTM	ArCOV-19 [51]	0.86	0.85	0.85	0.85
[52]	2021	High-order graph neural network (K-GNN) and graph attention network (GAT)	Chinese_Rumor_Dataset	0.92	0.82	0.80	0.80
[53]	2021	CNN with a Source-Replies conversation Tree	PHEME [14]	-	0.85	0.95	0.90
[54]	2020	CNN and Deep Transfer Learning	YELP-2 [53] and Five Breaking News (FBN) [55]	0.87	0.79	-	0.82
[56]	2020	Attention based LSTM	PHEME [14]	0.88	0.88	0.88	0.88
[57]	2019	Vanilla RNN and LSTM.	PHEME [14]	-	-	-	0.795
[58]	2019	Gated Recurrent Unit (GRU) with self-attention	Weibo [15]	0.96	0.98	0.98	0.96
[59]	2008	CNN and long-short term recurrent neural network.	Zubiaga et al [y]	0.82	0.44	0.40	0.40

5. Conclusion

As much as social media has become a precious source for sharing knowledge, it is also fertile environment for rumors. Early detection of online rumor posts has become urgent necessity. Current machine learning rumor detection technology demonstrated their efficiency. Machine learning techniques such as clustering, SVM, Naïve Bayes, KNN and deep learning algorithms have been found to be effective in rumor detection regardless of the increasing volume of rumors in social media platforms. Features for detecting rumors has been reviewed and enhanced to facilitate the rumor detection process. In this survey, we reviewed various research works on rumors detection in social networks. Furthermore, we summarized some recent literature on rumor detection based on classical machine learning and deep learning models along with the best performance measures recorded.

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