International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

The Detection of Twitter Trolls Interventions Using Machine Learning Algorithms

Hayder H. Safi

Submitted: 14/07/2023 **Revised**: 08/09/2023 **Accepted**: 25/09/2023

Abstract: Media campaigns, amplifying political events, and cyberbullying have become commonplace in the world of social media. To protect our societies, disinformation detection is a critical challenge in combating the spread of false information on social media platforms. Several machine-learning methods have been employed in troll detection to classify and identify troll accounts on social media platforms. On the other hand, there is a lack of research that is aimed to detect and characterize the activities of these accounts. In this paper, an adaptive algorithm is proposed to classify Twitter hashtags if they are normal and clean from Trolls' interventions or if there are direct amplifying and suspicious activities in them. A new set of relevant features are designed and proposed to be used with the machine learning algorithms. Our experimental results show that the proposed features with Artificial Neural Networks obtain the best results and can reach an accuracy of 91%. We believe that this algorithm can be of great value for governments and decision-makers to not be affected by social media campaigns powered by troll groups and be able to filter these disinformation campaigns easily.

Keywords*: Disinformation, Troll activities detection, Troll farms, amplifying political campaigns*

1. **Introduction**

Social media networks are websites or platforms that allow users to connect with each other and share information. They are a way for people to stay in touch with friends and family, meet new people, and learn about different topics. Some of the most popular social media networks include Facebook, Twitter, Instagram and TikTok. Recently, social media networks have become an essential part of our lives that reflect and affect our communities, attitudes, ideas, and even our feelings [1].

Twitter is a social media platform that was founded in March 2006 by Jack Dorsey, Noah Glass, Biz Stone, and Evan Williams. After signing up on this platform, users can post short messages, called tweets. Tweets can be up to 280 characters long and can include text, photos, videos, and links. Users can follow other users to see their tweets in their feeds, and they can also reply to tweets, retweet them, or like them. Twitter has been created to be used for a variety of purposes, including staying up to date on the news, connecting with friends and family, following your interests such as celebrities, athletes, musicians, and other people whom you admire, and engaging in conversations with people from all over the world. As of January 2023, Twitter has over 330 million active users which makes it one of the most popular and active social media websites [1, 2].

The widespread popularity of Twitter makes it has a significant impact on political situations and elections. It has been used to spread information, organize protests, and mobilize voters in many countries [3]. Politicians and political parties can use Twitter to share their views on current events, announce policy changes, and respond to criticism. Twitter can also be used to share news and information about political events. Due to this high impact of Twitter on political societies, some of the potential risks and bad impacts on political situations and elections have been noted and detected in recent years in many countries [4, 5].Examples of these risks include: -

- The spread of misinformation: Twitter can be used to spread misinformation, which can have a negative impact on political discourse.

Department of Computer, College of Basic Education
Mustansiriyah University
Baghdad, Iraq
hayder.h.safi@uomustansiriyah.edu.iq

- Political polarization: Twitter can be used to polarize voters, which can make it more difficult for them to find common ground.
- Cyberbullying: Twitter can be used to bully and harass political figures, which can have a chilling effect on free speech.

After the intense disinformation campaigns that recently start appearing before elections and political events, new terms have been raised to dialogize the origin of these campaigns which are *Trolls* and *Troll Farms* [6]. A Twitter troll account can be defined as a fake or real account that is used to post inflammatory, off-topic, or disruptive messages on the platform. The goal of a troll account is to provoke others into displaying emotional responses, or manipulating others' perceptions, thus acting as a bully or a provocateur. The behavior is typically for the troll's amusement, or to achieve a specific result such as disrupting a rival's online activities or purposefully causing confusion or harm to other people [7].On the other hand, a Twitter troll farm is a group of people who are paid to post inflammatory, off-topic, or disruptive messages on Twitter. The goal of a troll farm is to manipulate public opinion or disrupt online discourse. Troll farms are often used by governments, political parties, or businesses to spread propaganda or attack their opponents [8]. Troll farms are typically organized into teams of people who are responsible for different tasks, such as creating fake accounts, posting tweets, and responding to comments. The tweets posted by troll farms are often designed to be attention-grabbing and to provoke emotional responses from people. They may also contain false or misleading information [9].

The main focus of this paper is to identify and detect the interventions of these Troll farms on Twitter during political activities or political crises. Although there is a large research work on how to classify Twitter accounts into troll accounts or normal accounts, there is a lack of research on how to detect if the current trending topics are normal or amplified by some groups of Troll farms. To conduct this research, we gathered a large dataset of hashtags data from Twitter including tweets, retweets, replies, and user information. A set of effective and accurate features are proposed to be used to detect propaganda and interventions made by the troll accounts. Then, a set of machine learning algorithms are employed to detect if the considered hashtag or trending topic is normally trending or if it is among the campaigns carried out by Trolls farms. Since most propaganda and disinformation campaigns have been done by parties and governments, our research work focuses on a type of Trolls called state-backed or state-sponsored Troll groups.

The rest of this paper is organized as follows: Section two summarizes the research on detecting propaganda and disinformation on Twitter. Section three describes our methodology and algorithms used to accomplish the considered research task. The results and discussions are given in Section four. Section five concludes the paper and proposes some future works.

2. Related Work

By reviewing the literature, we can note that most of the research topics on Twitter trolls have been conducted on how to detect these groups and identify them rather than detecting their activities. Detecting disinformation campaigns on social media can be challenging, as it often involves analyzing large amounts of data and identifying patterns of misinformation or coordinated efforts. However, there are several approaches and techniques that can help in this process. This section is a summary of the current state of research on troll activity detection, highlighting various approaches and techniques employed in this field.

Characterizing Trolls is one of the most popular approaches to detecting the activities of Troll groups and accounts. Numerous studies have focused on understanding the characteristics and behaviors of trolls. Cheng et al. [10] identified key traits such as high posting frequency, use of profanity, and derogatory language. Wu et al. (2018) [11] explored the psychological aspects of trolling, emphasizing the role of anonymity and disinhibition.

Linguistic analysis is the second approach used to detect disinformation on Twitter and other social media accounts. Linguistic features have been widely used to detect troll activities. Rösner et al. [12] proposed a method based on stylometric analysis to identify trolls by their writing style and vocabulary usage. In 2016, Nobata et al. [13] utilized a set of machine-learning techniques to identify troll comments based on lexical and syntactic features.

Another approach is the social network analysis. Troll activities often involve networked behavior.

Gao et al. (2018) [14] analyzed the structural properties of troll communities and proposed a method to detect trolls based on network centrality measures. In addition, Lee et al. [15] investigated the propagation patterns of troll content and developed algorithms to identify influential trolls.

Machine learning algorithms have been widely employed for troll activity detection. As an example, Ghosh et al. [16] used supervised learning techniques to classify trolls based on linguistic and behavioral features. Where Zhou et al. in 2019 [16] proposed an ensemble learning approach combining multiple classifiers to enhance troll detection accuracy. In the literature, there are many other machine-learning algorithms utilized to identify the Troll's activities such as Support Vector Machines (SVM) [17], Random Forests [18], Naïve Bayes [19], and Neural Networks [20].

Deep learning models, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based architectures, have been utilized in disinformation detection tasks. CNNs capture local features and patterns in textual content, RNNs model sequential information, and Transformer-based models capture contextual information, enabling more accurate disinformation detection [21][22]. As an example, Zhang et al. employed a deep neural network to detect trolls by capturing linguistic patterns and contextual information [23]. Nguyen et al. applied transformer-based models to identify troll accounts through their posting behavior [24]. Disinformation detection often requires analyzing multiple modalities, including text, images, and metadata. Deep learning techniques have been extended to handle multimodal data by integrating multiple neural networks or designing joint architectures. This enables leveraging complementary information from different modalities for improved disinformation detection accuracy [25][26].

Furthermore, deep learning models excel at learning meaningful representations from textual data. Word embeddings, such as Word2Vec and GloVe, are commonly used to transform text into dense vector representations. These embeddings capture semantic and syntactic relationships, enabling deep learning models to capture nuanced patterns and contextual information in disinformation detection. Examples of these approaches were proposed in [27] and [28].

Analyzing user behavior patterns can also provide insights into troll activities. Stringhini et al. [16] studied the temporal dynamics of trolls' posting behavior and proposed an approach based on activity bursts for troll detection. Xu et al. [23] analyzed the interaction patterns between trolls and other users to identify suspicious accounts.

Several studies have proposed ensemble approaches combining multiple detection methods. Kumar et al. [29] proposed an ensemble of classifiers based on linguistic, behavioral, and network features for troll identification. Mishra et al. [30] developed an ensemble model incorporating textual, behavioral, and social network features for improved troll detection.

In other research, transfer learning, using pre-trained deep learning models on large-scale datasets, has proven beneficial in disinformation detection tasks. Pretrained models, such as BERT, GPT, or VGG, provide powerful feature representations that can be fine-tuned on smaller disinformation detection datasets. This approach enables leveraging prior knowledge from general domains, improving the generalization and efficiency of disinformation detection models [31].

3. Proposed Methodology

The proposed algorithm is designed to take a hashtag as an input parameter and after downloading the data and processing it, the output will be the estimated percent that reflects the size of abnormal external interference on this hashtag. As we discussed before, the proposed algorithm will give valuable information to decision-makers and politicians regarding the real situation and help them understand the actual situation without amplifying or exaggerating.

Figure 1 shows the main steps of our algorithm. First, after feeding the algorithm with the hashtag name, it will download the data of this hashtag. The downloaded data includes information on tweets, retweets, replies, and users. After that, the data will be cleaned by deleting the unimportant and redundant features from the data. In this step also the algorithm extracts the features that need to be processed before being used as we will explain in the next subsection. To classify the considered hashtag, if it is normal or suspicious, a machine learning algorithm should be selected. In this paper, the Artificial Neural Network (ANN) is used. As with any machine learning algorithm, it should be trained first using a part of the input dataset and then it can be used to classify hashtags.

Features Description

Detecting Trolls' activities typically involves analyzing various features related to different categories such as user behavior, linguistic patterns, and network characteristics. While the specific set of features can vary depending on the approach and context, in this paper we generated new features by utilizing and enhancing some commonly used features for troll detection. It's important to note that troll detection often involves combining multiple features and employing machine learning algorithms or rule-based systems to classify and identify troll behavior accurately. The description of the selected features is given bellow: -

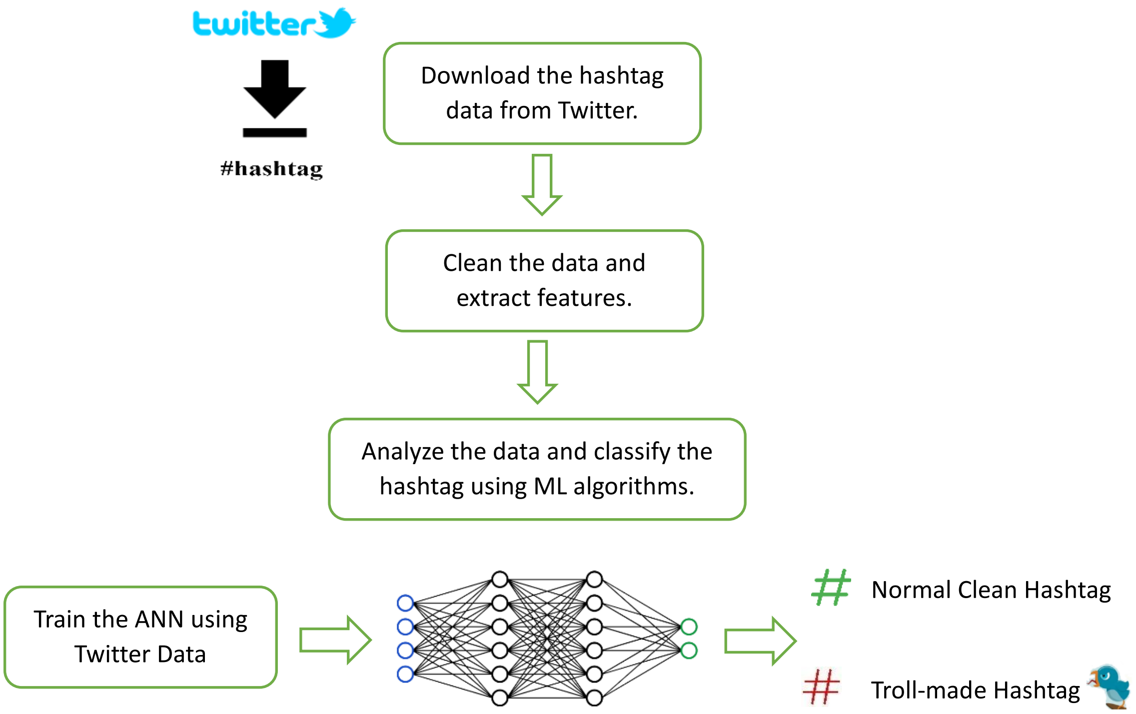

Fig. 1: The steps of the proposed troll activities detection algorithm

Percent of new users/Accounts:The percentage of new users or accounts participating in a Twitter campaign can potentially indicate suspicious troll activities in a trend. Determining if an account is new or not depends on its creation date and it can be considered using a fixed period depending on the country and the context. It should be noted that any algorithm cannot solely rely upon this measure. It is one of the factors that can be considered as part of a broader analysis in troll activitydetection. In some cases, a high percentage of new users may be normal if the campaign targets a particular demographic or aims to attract new participants. However, if the campaign involves a highly controversial or polarizing topic, an abnormally high percentage of new accounts might indicate coordinated trolling or manipulation. In addition, If a significant number of accounts are relatively new and were created around the same time or in a short period, it might suggest the possibility of troll or bot accounts that were created for the specific purpose of participating in the campaign.

Percent of users with more than 10 tweets in the first trending hour:A high number of users with a significant number of tweets (more than 10) participating in a campaign might raise suspicions, especially if the campaign is short-lived or focuses on a specific topic. Trolls often exhibit high posting frequency to amplify their messages or disrupt conversations.

Percent of tweets tweeted by suspicious accounts: After determining the suspicious account as described in the previous point, it is important to calculate the percentage of tweets that generated/posted by these accounts. This feature not only identifies the external interventions in a campaign but also can estimate the size of the intervention which can be a very important for decision makers.

Percent of retweets tweeted by suspicious accounts: this feature is the same as the previous feature where it is computed based on retweets rather than tweets. Troll accounts can exhibit various posting behaviors in campaigns, including both making tweets and engaging in retweets. However, the specific posting behavior of troll accounts in campaigns can vary depending on their objectives, strategies, and the nature of the campaign itself. The difference between tweets and retweets is discussed here: -

- Tweeting Behavior: Troll accounts may actively create and post original tweets in a campaign. They might use these tweets to spread false information, promote divisive narratives, provoke reactions, or amplify certain viewpoints. Trolls may employ aggressive or inflammatory language, target specific individuals or groups, or attempt to manipulate public opinion through their own content.
- Retweeting Behavior: Troll accounts can also engage in retweeting other users' content within a campaign. Retweeting allows trolls to amplify certain messages, support narratives aligned with their objectives, or propagate misinformation by spreading content from other accounts. By strategically retweeting influential or provocative content, trolls aim to increase the visibility and reach of ideas or create a sense of consensus or controversy around certain topics.

Volume of tweets just after the trend:The number of tweets just after a hashtag trend can provide some insights into the nature of the trend. Genuine trends often have a sustained presence and engagement over time, while manipulated trends driven by troll accounts may experience a rapid rise and fall in tweet volume.Hashtags typically become trending topics on social media platforms like Twitter when a significant number of users include the same hashtag in their tweets within a specific timeframe.In rare cases, groups of Trolls or automated systems may attempt to artificially manipulate hashtag trends. This can involve the use of bots or coordinated efforts to create the appearance of a trending hashtag without genuine user-generated content. Such manipulation tactics are against platform policies and are actively monitored and addressed by social media platforms.

Ratio of retweets to tweets:Troll accounts often seek to amplify certain messages, narratives, or misinformation. They may use retweets as a strategy to spread content widely and increase its visibility. As a result, troll accounts tend to have a high retweet-to-tweet ratio, indicating a significant focus on sharing and amplifying others' content rather than generating original tweets.

4. Results

In this section, we describe in detail how the dataset is gathered from Twitter and then give our experiments' results.

4.1 Data Gathering

The dataset used in this research is gathered from the Twitter platform only. To gather a dataset from Twitter for hashtag analysis, firstly a Twitter API Accesscredentials should be obtained from the Twitter development portal. After that the criteria for the tweets wanted to be collected are specified. This includes the hashtag(s) we want to analyze, the time frame of the tweets to retrieve, and any additional filters such as language or geographic location.The tweets that match our criteria are retrieved using the API connection and the defined query parameters. We can iterate through the results to collect the desired information, such as the tweet text, timestamp, user information, engagement metrics, and other relevant metadata for preliminary analysis. The collected data is then stored in a structured format, such as a CSV or JSON file, for further machine learning analysis. To simplify the data-gathering task, we used KNIME data science tool. It is an open-source data analytics and machine learning platform. The name "KNIME" stands for "Konstanz Information Miner," referring to its origins at the University of Konstanz in Germany. KNIME provides a visual interface that allows users to create data workflows by connecting nodes representing data processing and analysis operations [32].

In this paper, the data of 160 hashtags is gathered and stored. Table 1 shows some statistics about the collected dataset. Table 2 shows some hashtags examples. Note that most of the hashtags were collected during some political crises to ensure a convenient environment for troll groups.

Table 1: Statistics of the collected dataset

Number of Hashtags	160
Number of Tweets	1499375
Number of Users/Accounts	394799
Number of countries	12
Languages	EN-AR-TR-HI
Tweets Time	20-7-2022 – 6-11-2022

Table 2: Examples of the selected hashtags

Hashtag	Trending Date	Trending Country
#كفاكم_هدما_لقيمنا	2022-10-28 17:00	Qatar
#كلنا_بصوت_واحد_ننتخب	2022-10-31 11:00	Bahrain
#TrudeauWasRight	2022-10-28 23:00	Canada
#JUSTINflation	2022-09-2911:00	Canada
#إطلاق_استراتيجية_ساقي	2022-09-29 12:00	Saudi Arabia
#موازنه_المسخره	2022-09-26 17:00	Lebanon

4.2 **Results and Discussions**

In the first experiment, we show some statistics regarding the number of tweets and retweets related to some hashtags. Figure 2 shows the results of this experiment. To make it clear, for every hashtag after the data is downloaded and cleaned, the tweets and retweets are separated from each other. As discussed in the previous section, this is because tweets and retweets are used differently by troll groups depending on the goal and other factors. After that, the tweets and retweets are grouped by the "USER ID" or "User Screen name" features. As a result, the number of tweets and retweets that every user posted on the considered hashtag is computed. As can be seen in Figure 2, when there is intervention from troll groups, it is noted that some accounts post more than 900 tweets/retweets to affect public opinion or the real campaign. It is noted also that the histogram of the users has a sharp fall which differentiates the normal users from suspicious users and also confirms the external interventions.

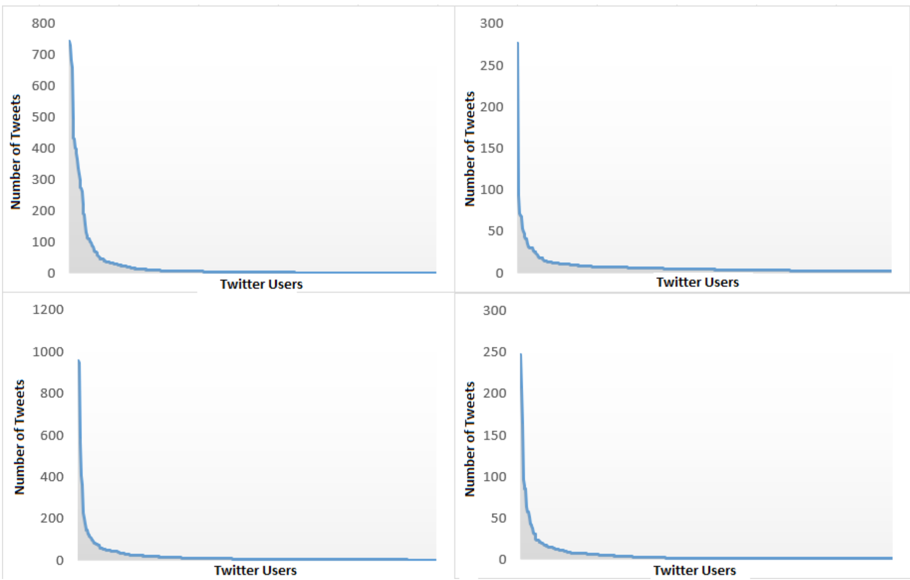

Fig. 2: The results of 4 different (Troll-made) selected hashtags from our dataset.

On the other hand, Figure 3 shows the results of repeating the same experiment but with normal hashtags this time. As clearly seen from the figure, in normal hashtags the number of tweets every user does falls gradually without a sharp fall as in troll-made campaigns (see Figure 2). At the same time, the highest number of tweets that have been done is around 38 which is much less than in the case of trolls-made scenarios

.

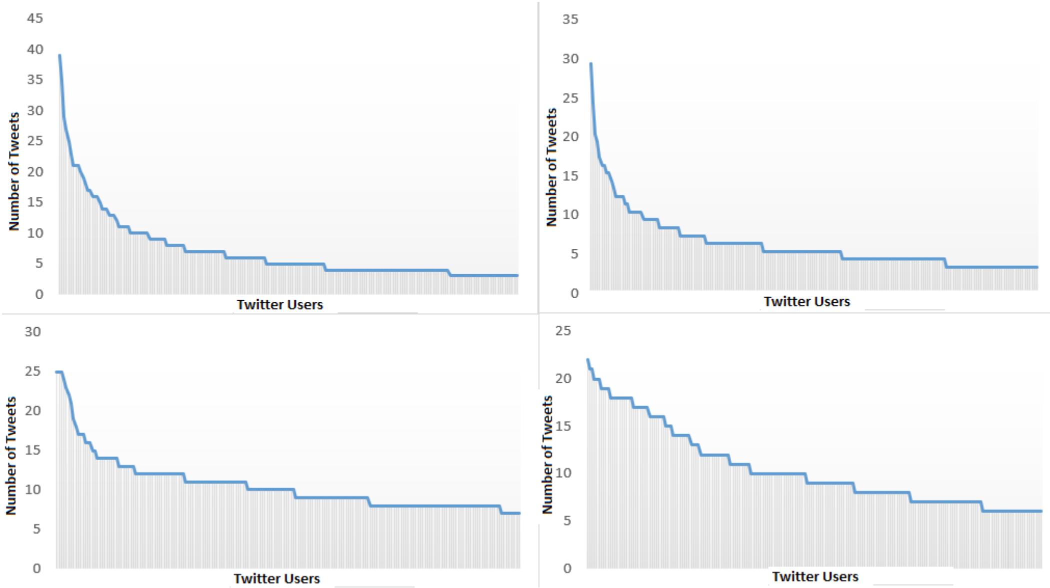

Fig. 3: The results of 4 different (normal) selected hashtags from our dataset

The results of applying the proposed algorithm to the gathered dataset are summarized in Table 2. The results show that the ANN algorithm with the proposed new features can classify hashtags with an accuracy of more than 91%. This output reflects the effectiveness of the proposed features which makes the algorithm able to characterize the hashtags when there are suspicious activities or external interventions from troll groups.

Algorithm	Accuracy
ANN	91%
SVM	88%
NB	74%

Table 2: The accuracy of the proposed approach using different machine learning algorithms.

5. Conclusion

This paper aims to identify and detect the interventions of Troll group accounts on Twitter during political activities or political crises. Although there is a large research work on how to classify Twitter accounts into troll accounts or normal accounts, there is a lack of research on how to detect if the current trending topics are normal or amplified by some groups of Troll farms. To do this research, a large dataset of hashtag data was collected from Twitter using Twitter API and KNIME tools. The collected data includes tweets, retweets, replies, and user information. A set of effective and accurate features were proposed and utilized to detect the different types of propaganda, disinformation, and interventions generated by the state-backed troll groups. Then, a set of machine learning algorithms were employed to detect if the considered hashtag or trending topic is normally trending or if it is among the campaigns carried out by Trolls farms. Our experimental results showed that the proposed features with Artificial Neural Networks obtained the best results with an accuracy of 91%. As a part of our future work, we plan to increase the number of features and embed more relation features that consider the relationship between Twitter accounts.

References

[1] Kwak, Haewoon, Changhyun Lee, Hosung Park, and Sue Moon. "What is Twitter, a social network or a news media?." In Proceedings of the 19th international conference on World wide web, pp. 591-600. 2010.

[2] Weller, Katrin, Axel Bruns, Jean Burgess, Merja Mahrt, and Cornelius Puschmann, eds. Twitter and society. New York: Peter Lang, 2013.

[3] Sahmoud, Shaaban, and Hayder Safi. "Detecting suspicious activities of digital trolls during the political crisis." In 2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies (ICIoT), pp. 532-537. IEEE, 2020.

[4] Wolfsfeld G, Segev E, Sheafer T (2013) Social media and the Arab spring: politics comes first. Int J Press Politics 18(2):115–137.

[5] Enjolras B (2002) How politicians use Twitter and does it matter? The case of Norwegian national politicians. Institute for Social research, Oslo

[6] Sahmoud, Shaaban, Abdelrahman Abdellatif, and Youssof Ragheb. "A Fast Algorithm for Hunting State-Backed Twitter Trolls." In Pervasive Computing and Social Networking: Proceedings of ICPCSN 2022, pp. 643-657. Singapore: Springer Nature Singapore, 2022.

[7] Zannettou, Savvas, Tristan Caulfield, Emiliano De Cristofaro, Michael Sirivianos, Gianluca Stringhini, and Jeremy Blackburn. "Disinformation warfare: Understanding state-sponsored trolls on Twitter and their influence on the web." In Companion proceedings of the 2019 world wide web conference, pp. 218-226. 2019.

[8] Engelin, Martin, and Felix De Silva. "Troll detection: a comparative study in detecting troll farms on Twitter using cluster analysis." (2016).

[9] McCombie, Stephen, Allon J. Uhlmann, and Sarah Morrison. "The US 2016 presidential election & Russia's troll farms." Intelligence and National Security 35, no. 1 (2020): 95-114.

[10]Cheng, J., Danescu-Niculescu-Mizil, C., & Leskovec, J. (2017). Antisocial behavior in online discussion communities. ICWSM, 17, 186-195.

[11] Ghosh, S., Surana, A., & Kate, A. (2017). Understanding and combating link farming in the twitter social network. IEEE/ACM Transactions on Networking, 25(6), 3659-3672.

[12] Gao, W., Wilson, C., Li, Y., & Zhao, B. Y. (2018). Trolls and polarization dynamics in the 2016 US presidential election. ICWSM, 18, 386-395.

[13] Lee, K., Lee, S. W., & Kim, J. (2019). Trolls spreading violent extremist narratives on Twitter: Network characteristics and influence mechanisms. Computers in Human Behavior, 96, 173-183.

[14] Nobata, C., Tetreault, J., Thomas, A., Mehdad, Y., & Chang, Y. (2016). Abusive language detection in online user content. Proceedings of the 25th International Conference on World Wide Web, 145-153.

[15] Rösner, D., Scholz, C., & Stieglitz, S. (2018). Spotting the troll: Stylometric analysis of social media users. Computers in Human Behavior, 80, 209-217.

[16] Stringhini, G., Kruegel, C., & Vigna, G. (2017). Detecting spammers on social networks. IEEE Transactions on Dependable and Secure Computing, 14(2), 175-189.

[17] Mishra, A., Shrivastava, M., & Jaiswal, A. (2019). Fake user detection on social media using machine learning and sentiment analysis. 2019 3rd International Conference on Computing, Communication, Control and Automation (ICCUBEA), 1-6.

[18] Shu, K., Wang, S., Liu, H., & Lee, D. (2017). Trolls and their impact on social media sentiment analysis: A case study on college students' evaluations of teachers on RateMyProfessors.com. Decision Support Systems, 99, 75-83.

[19] Burnap, P., Rana, O. F., Avis, N., & Williams, M. (2015). Cybercrime and the web: An ecological approach to predicting and preventing online trolling. ACM Transactions on Management Information Systems, 6(2), 1-31.

[20] Badjatiya, P., Gupta, S., Gupta, M., & Varma, V. (2017). Deep learning for hate speech detection in tweets. Proceedings of the 26th International Conference on World Wide Web, 759-760.

[21] Zannettou, S., Bradlyn, B., De Cristofaro, E., Kwak, H., Sirivianos, M., Stringhini, G., & Blackburn, J. (2019). Disinformation warfare: Understanding state-sponsored trolls on Twitter and their influence on the web. ACM Transactions on the Web (TWEB), 13(2), 1-30.

[22] Shu, K., Wang, S., Liu, H., & Lee, D. (2019). Understanding user behavior and sentiment in social media during social crises: A deep learning approach. Information Sciences, 484, 187-203.

[23] Wu, J., Schild, L., & Onnela, J. P. (2018). Understanding psychological processes underlying engagement in trolling. Human Behavior and Emerging Technologies, 1(1), 59-67.
[24] Xu, W., Zhang, Y., Zhang, Y., & Chen, J. (2018). Suspicious user detection in online social networks via similarity learning. ACM Transactions on Intelligent Systems and Technology, 9(1), 1-21.
[25] Islam, M. R., & Inkpen, D. (2018). Automatic detection of fake news. In Proceedings of the 27th International Conference on Computational Linguistics, 3391-3401.
[26] Khoo, Y. H., Cai, B., & Zhang, Y. (2020). Multi-modal approach to fake news detection using multimodal ensemble deep learning. Knowledge-Based Systems, 196, 105781.
[27] Potthast, M., Köpsel, S., Stein, B., & Hagen, M. (2018). A stylometric inquiry into hyperpartisan and fake news. arXiv preprint arXiv:1801.03524.
[28] Benites, F., Guevara, S., Rosso, P., & Montes-y-Gómez, M. (2021). Towards disinformation detection: A case study on the COVID-19 pandemic. Information Processing & Management, 58(2), 102582.
[29] Zhang, Y., Robinson, D., & Mao, J. (2020). Detection of malicious user accounts in online social networks using deep neural networks. IEEE Transactions on Information Forensics and Security, 15, 2126-2139.
[30] Zhou, C., Zhang, Z. K., Yang, Z., & Yu, P. S. (2019). Ensemble-based trolling behavior detection in social media. Knowledge and Information Systems, 59(2), 445-470.
[31] Cruz, Jan Christian Blaise, Julianne Agatha Tan, and Charibeth Cheng. "Localization of fake news detection via multitask transfer learning." arXiv preprint arXiv:1910.09295 (2019).
[32] Jagla, B., Wiswedel, B., and Copp´ee, J. Y. (2011). Extending KNIMEfor next-generation sequencing data analysis. Bioinformatics, 27(20),2907-2909.
[33]Dr. B. Maruthi Shankar. (2019). Neural Network Based Hurdle Avoidance System for Smart Vehicles. International Journal of New Practices in Management and Engineering, 8(04), 01 - 07. https://doi.org/10.17762/ijnpme.v8i04.79
[34] Archana, M., Kavitha, S., & Vathsala, A. . (2023). Auto Deep Learning-based Automated Surveillance Technique to Recognize the Activities in the Cyber-Physical System. International Journal on Recent and Innovation Trends in Computing and Communication, 11(2), 35–42. https://doi.org/10.17762/ijritcc.v11i2.6111