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Fake News Detection of COVID-19 on Twitter Platform: A Review

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Abstract:

In the 21st century, it was found that rather than conventional media such as print media, a larger number of participants consumed news from search engines and social media. The goal of this research is to examine the false news on the Twitter platform connected to COVID-19. A difficult task for humans is to recognize such false facts. Many researchers faced difficulties to identify the issue statements and their attributes in describing fake news. Attempts have been devoted to addressing this issue with techniques of deep learning and machine learning. In fake news identification, the effect of linguistic features and contextual characteristics areanalysed and some techniques such as Naive Bayes, Decision tree, Hybrid CNN, KNN, and SVMare compared. This study reviewed the current and past literature suggested by the researchers to detect fake news.Approaches are based on content types (textual or image-based) to overcome the problem more smartly and to achieve enhanced classification results.The main purpose of this paper is to review literature for COVID-19 fake news detection on Twitter using machine learning and deep learning method.

Keywords **—Machine Learning Methods, Fake News Detection, Natural Language Processing, Deep Learning Methods.**

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I. INTRODUCTION

Ensure the validity of evidence has been an important concern that has harmed social implications. When there are still many people relying on access to information and news on social media, news publishers no longer have the power to distribute content. In the light of changes the world is currently facing, a growing array of everyday activities are going online, including reading news and being up-to-date. The growth in the amount of information made available has contributed to the propagation of false news becoming a trend-setting subject on the Internet. Recent incidents, such as the COVID-19 pandemic, have demonstrated that false news has a major negative effect on communities by exposing reports that do not report reality.In comparison, false news is used to misinform and exploit people's views for a variety of reasons.Authors are also emotionally marked, ambiguous, and they often contain several grammatical errors. The identification and detection of spam are close to the misleading detection system.

Significance

Social media platforms create less communication gap between people. Theycan easily exchange important messages through these media platforms, such as Facebook, Instagram, and Twitter. But some people use these platforms for fake communication(like a politician, medicine companies and businesses).This fake communication makes it hard for people to recognize between the true and false news. The false news on the all-social site must be recognized. Nowadays, all in the word COVID-19 virus but some fake news include. Today's COVID-19 virus spread all around but mostly included the fake news with real lines. There is no extra information on the social platform, the way people have been told that this is true or tillage.

II. Background

Significantly,the World Wide Web advanced after the mid-1990s people communicate with each other's using online available social media: Twitter, Facebook is a source of distribution of information all over the world. Due to their characteristics like low cost and easy to use it become a big platform in which people can interact with each other and share their knowledge and information. however, as the popularity of social media is increasing and the internet has become the ideal fertile place where fake news spread very quickly and fast like fake reviews, fakepolitical statements, wrong information, fake advertisement, wrong Knowledge, etc. Now social media has become popular for fake news spreading than mainstream media.

However, all this misleading information and fake news which is widely spread because different facts and problems for both industry and users now become the major concern for all. Furthermore, a huge amount of misleading information is spread through and created on daily basis on the internet which also a potential thread for online communities. This issue gains the attention of both researchers and practitioners especially after 2016.

In today's society, the identification of fake news is critical as the latest news content is quickly generated as a result of the proliferation of technology. There are seven key groups within the world of false news, and within any of the groups, the item of false news material is often visual- and/or linguistic-based. Thus, both linguistic and non-linguistic signs are also analyzed using many techniques when identifying false news. Although many of these approaches are usually effective in identifying false news, they also have some drawbacks. With the approach of the computer, a linguistic cue is identified. They intended to create a hybrid approach that blends language and machine learning with network-based behavioral knowledge for the methods. Besides, underneath the linguistic cue method, related data analysis, and social network behaviors underneath the network analysis method, they must define deep syntax interpretation and semantic analysis.

Now a year, there are effective frameworks that are established to help the online user by detecting fake and misleading news. However, features like news patterns and new author credibility play a very important role to predict the online available fakeness. Online available social data is also time-sensitive like they are real-time occurrences.

What is Fake News?

Fake news is incorrect or misleading facts identified as social platform news. It also seeks to destroy the image of an individual or entity or to make money from advertisement sales.

III. Literature review

The purpose of this literature review is to collect the different work which is done in the area of detecting fake news. The scholarly work shows that misleading information and news have now become a major issue amongst scholars from different backgrounds. The structure of this study is:

- **Fake news detection on social media**
- **Fake news detection of COVID-19**
- **Fake news detection of COVID-19 on Twitter**

Fake news detection on social media

Research produced an auto false news identification system based on a deep geometric learning approach using a Twitter dataset [1]. Naturally, the proposed approach enables heterogeneous data to be aggregated relating to user account and engagement, the layout of the social network, news spreading patterns, and material. As compared to 'hand-carved' functionality, the main advantage of using a deep learning approach can understand the data which are related to task-specific features. In this situation, the option of deep geometric learning is inspired by the data's graph-structured existence. Through the different pre-processing techniques of NLP done with backward feature selection and feature extraction through important attributes. The preprocessed data then fed into geometric deep learning methods CNN and SELU. The results show that accuracy is 92.7% with CNN and 88.30±2.74% in SELU, CNN achieved better accuracy rather than SELU. In the future, adversarial approaches could shed light on the decision-making phase of the neural graph network, leading to improved interpretability of the model [1].

Build LSTM focused on machine learning strategies for semantic false news identification [2]. A semantic false news identification system developed on contextual features such as expectations, identities, or statistics derived directly from the text. Pre-processing is done with text clean-up, stop words removal, tokenization, marks have been encoded using label encoder, transforming the texts into sequences and padding. Apply on liar datasets and PolitiFact dataset for the performance. Experiments focus on brief texts of differing degrees of truths which show proves that adding semantic functionality greatly increases exactness. Future areas of study include the exploitation of these relational functions along with graph neural networks, such as the newly created R-GCN [2].

Execute an implicit or explicit analysis of functionality to define a collection of possible user identities for the identification of fake news [3]. Nowadays, quality news is perceived to be poorer than conventional news, resulting in vast quantities of false news. Identify consumer groups based on the level of confidence in news and analyze the connection in the middle of user accounts and fake/real news. For pre-processing, a correlation-based collection of features is used. Build real-world databases to calculate consumer confidence level for recognition, and pick representative classes of all "experienced peoples who can fake stories as inaccurate versus "naive" consumers, who are most willing to indulge in misleading news. As a result, specific people are most likely to believe that false news than actual news. However, the current approach also needs to explore how well these functions could be aggregated into a misinformation identification framework to advance the analysis of fake news detection [3].

Proposed a machine learning ensemble method that is used to describe which detect the false news [4]. Using the two datasets ISOT fake news dataset, Kaggle's involves the extraction of linguistic features including the n-grams from textual papers and practice of various ML models such as KNN, LR, LSVM, DT, XGBoost, and RF. Pre-processing is done by with unwanted variable removed article with less word and nobody text is removed, multicolumn transformed in a single column, features extraction by using LIWC2015 tool, data scaling in range of (0,1), data splitting with the ratio of 70/30. The best results have been obtained by XGBoost. The average booster classifier XGBoost for all datasets is 95.25 percent, the random forest RF is 79.75 percent, the logistic regression is relatively easier, but the average exactness is over 90 percent. The maximum exactness is obtained on ISOT false information dataset is 99 percent, with the RF algorithm and also Perez-LSVM. But the detection of key factors engaged in the distribution of news is an essential move in some of the problems that demand an order to minimize the propagation of false news. Graphics philosophy and machine learning methods may be used to classify the primary outlets involved in the propagation of false news [4].

Using a supervised artificial intelligence algorithm to identify fake news on social media [5]. Pre-processing is done by with extract numbers from text data, extract characters punctuation from text information, filter characters containing character < N, add case translate to text data, delete stop phrase, stem text information code mining techniques has been an appeal to the internet news information collection in the first phase of that work. The goal of text analysis approaches and methods is to extract structured data from a nonstructured news document. In the next stage, supervised AI algorithms BayesNet, decision tree, OneR, judgment stump, CVPS, RFC, LWL, WIHW, bagging, OLM, SGD, JRip, CvC, simple cart, MLP, J48, SMO, ZeroR, IBk, LMT, ASC and KLR refer to three datasets, textual results, BuzzFeed political news data set, ISOT false news information set and random political news information set. Structured news datasets are included. The better mean values for accuracy, exactness, and F-measurement are derived from its decision tree algorithm. For the strongest accomplishment of the future, collection methods, and the various function extraction methods can be used [5].

Proposed a FANG, a new graphical social contextual description & knowledge system for false report identification [6]. In past context models of targeted results, the emphasis is now on representation learning. Pre-processing is done with attribute extraction from social actors, PCA for in-depth assessment, projections by analyzing concrete experiments, fact-checking organization, and the record of accurate rejection. Methods used for operating SVM models of TF.IDF, CSI, and GCN features. Experimental findings suggest that FANG is improved at seizing a high-fidelity image of the social meaning relative to previous graphic and non-graphic versions. But FANG is ascendable in practice, since it does not must to hold every node, and is effective at supposition moments, with no craving to reprocess the whole graph. Multitask learning to work together with activities like false news identification, source factual assessment, and echo chamber exploration can be used for future work [6].

Developing multimodal content in social media to spot fake news, integrating knowledge in various means of identifying false news, is a vital challenge in the modern media environment [7]. Pre-processing is done by with delete any irrelevant statistical hints from the text, debunking repository, and linguistic-based functionality. Using various approaches LSTM, GRU, CNN, Bert, MVNN, and attRNN for identification. These are in essence, fusion processes. In terms of exactness, Bert is marginally higher than other versions. More intuitively, attRNN suggests a neuron-level focus system to combine multimodal information. Create and release a multimodal data archive on fake information on the Weibo Social platform (MCGFNeWS) in the future to help assess the success of various methods by participants. Also, leave the guideline for potential researchers with this work [7].

Proposed a novel GNN based paradigm called Graph Comment user Advanced Learning (GCAL) for false news identification [8]. Fake news is a longer social issue in the media. Pre-processing is done with attentive learning based on text representation, network representation learning based on heterogeneous graph neural network, node features aggregation, high-level features extraction. That typically learn explicit and implied contextualized representation effectively in news content and user-comment connection. Apply the approach to two separate datasets, the PolitiFact dataset, and the gossip cop dataset. In terms of accuracy (at least 4 percent in Accuracy, 7 percent in the recall, and 5 percent in F1). Present findings suggest that the proposed GCAL has more unequal capabilities than the other versions. In the future, the use of the news spread path can be seen as a new form of connection in the graph. Next to integrate input from authoritative users for the collection of explanatory comments for the verification of false news. Second, the discovery on the path to using semi-supervised learning in our model to identify big unmarked news on various media networks [8].

The proposed mathematical model for the analysis of complex diffusion and even regulation of message transmitting activities in OSNs [9]. This would expert to identify and also remove false information from OSNs and support alleviate certain OSN users of pandemic tension. With statistical simulation replicate utilize MATLAB on a 3-GHz Intel Xeon device running UBUNTU 19.2 LTS as well 16-GB RAM. Unnecessary messages can scatter throughout the social network. The model is formulated using a system of differential equations. The findings could help to address some of the present global problems linked to the dissemination of fake information. In the future, the approach of latent and separation will be used to avoid the dissemination of gossip and the spread of false news from the internet network [9].

Proposed fake box model-assisted adversarial machine learning to detect false news on McIntire's dataset [10]. Pre-processing is done with the study of word patterns, statistical correlations of report papers, and linguistic features of reports. NLP models are used for training in a manually curated database. Fake box's accuracy on McIntire's data collection is 52.77 percent, the incorrect rate is 31.79 percent, and while the reverse is 15.44 percent. But the issue is purporting to distribute news from a different perspective. So, potential work involves creating a visualized interface for news information graph crowdsourcing, making work as simple as possible for non-experts, and avoiding fake news at an early point [10].

Introduced a novel automated false news authenticity inference model, and also introduces a brand-new diffusive unit model, in other words, to say that GDU [11]. The GDU model gains several stores from various root concurrently, including the false detector. Creator-Article publication historical documents, author credentials analysis with textual content, topic credentials analysis, and creator credentials analysis. Enabled by a community of specific and latent features derived from the textual content. Fake detector creates an in-depth diffusive network model for simultaneous reporting of posts, creators, and topics. The outcome GDU accepts several inputs from different sources simultaneously. Besides, the similarities between news stories, creators, and news subjects are supported [11].

Suggest the hypothesis that there is a connection between misleading messages or rumors and emotions about texts shared online [12]. Pre-processing is done with email sentiment analysis and text-based gossip identification. Applied separate LOGIT, SVM-Linear, decision trees, Random forest, XG-Boost, and LSTM methods for identification. Since using the PHEME named twitter dataset, there is a 3 percent increase to 89 percent where there is a mix of text and emotional ratio where there is an embedded picture in the post, but these additional features (AD) have not boosted the efficiency of the models. In the future, additional nostalgic sources derived from, e.g., photographs, embedded content in the image, or further visual media, including animations clips GIFs, and some other clips, can appreciate the performance of the model and are considered to appreciate the performance of the model [12].

Two methods detective and ICS are suggested [13]. Pre-processing is done by with divided data into two subsets: training and testing, with 70%-30% of the information. The accuracy of the ICS result is better than the detective process. BuzzFeed dataset and the PolitiFact datasets are used for experiments. Preliminary tests with two real-world databases are presented as proof that the proposed approach could identify false news without needing users' detailed knowledge about the news & information. Without undermining the classification results obtained by the state-of-the-art crowd signal system. The future analysis involves experimentation with different measurement standards, measures, and databases. As well as investigating multiple methods of supplying consumers with explicit feedback on news and comparisons with techniques other than crowd signals [13].

Created a special counterfeitinformation detector that utilizes restate attribute as a key attribute of Bayesian ML to evaluate the probability, that information of story is counterfeit through text blob, linguistic communication, and SciPy toolkits [14]. Pre-processing is done with the basic python and text blob method used to classify quotes, several quotes within a short distance of each other within a text, and quote attribution classifier. The locally generated dataset is used for experiments. The final average exactness of the classifier is 0.69 and thus the overall error of the classifier is 0.31. The resulting accuracy of the procedure is 63,333 percent successful in determining the probability that a quote editorial is false. Future expected research initiative entails combing the attribution quality removal. Along the other considerations that arise from the research to include information that not only recognizes possible false material but also affects content based on a reader's or aim demographic to build incorrect or modify decisions [14].

Aim to answer questions about the existence and scope of the interaction within user accounts on the internet and fake information, and offer an answer to use user profiles to spot fake news [15]. Pre-processing is done with register time (0.937), verified (0.099), political bias (0.063), personality (0.036), status count (0.035), and comparative analysis. Using different methods LIWC, RST for fake news detection. LIWC performs better than RST. Methods applied to the PolitiFact dataset, and gossip cop dataset. As the result, performance is over If only overt or implied attributes are considered. E.g., the F1 scores on All features indicate an improvement of 4.51 percent and 9.84 percent compared to explicit. In the future, explore the associations between suspicious accounts and fake news to mutually identify malicious accounts and false news products [15].

Proposed a novel social context-aware false news identification system, SAFER, focused on (GNNs) [16]. Pre-processing is done by removing more frequent/active users, aggregating information, and community features are combined with textual features. The results show to demonstrate that incorporating community-based modelling leads to significantly improved performance in this task as compared to a purely text-based framework. In the ensuing, it would be fascinating to apply these techniques to other tasks, such as detecting rumors and modelling changes in public beliefs [16]**.**

Evaluating the topic of false news on the scales of the information environment [17]. Pre-processing is done with data that are supplanted by elevated -level conception throughout the utilization of postulation hierarchies, consumption greatly, and given the massive differences in average news viewing. A list-based classification method is applied on a special multimode dataset containing a geographically stratified analysis of smartphone, internet, and TV use. The findings indicate that the roots of media disinformation and diffusion are most suitable to be in the features of ordinary information or to ignore reports entirely than they are in blatant fakes. In the future, disinformation and its highly corrosive impact on society should include all possible outlets of news that are troublesome, in addition to the lack of related content, not just the kind that is more readily detected and minimum linked to traditional media priorities [17].

Involve a debate on semantic cue and network analysis methods, and suggests a three-part solution utilize Naïve Bayes classifier, SVM, and also semantic analysis as effective by identifying bogus social media content [18]. Pre-processing is done with the degree of compatibility between a private experience, less effective on noisier datasets, linguistic cues, and network analysis approaches. The result suggested approach focuses on integrating the SVM and Naïve Bayes classifiers to achieve even more precise results. Test the suggested Naïve Bayes classifier, SVM, and semantic analysis system in the future, however, due to minimal expertise and time, this could be a project for the project's long-run direction [18].

Develop a unique algorithm, DETECTIVE, that performs Bayesian inference for the detection of fake information and also learns about the user flagging exactness over time [19]. Pre-processing is done by generating news every epoch, maximum spread at the subsequent time step t +1, robustness against spammers. All methods and pre-processing techniques are applied to the Facebook dataset. As a result, that algorithm uses posterior sampling to intentionally balance off manipulation (selecting information that enlarges target merit at a given time) and discovery (selecting information that enlarges the merit of information to learn related consumer flagging exactness). For the future, it would be helpful to increase our model approach and to infer the reliability of the sources. It will also be necessary to carry out usage studies by implementing our algorithm in an extremely real-world social system [19].

Performed three main approaches: content-oriented, metadata-oriented, and network interaction-oriented [20]. Pre-processing is done with remove I.P. and TJ (n=2773), remove missing DOIs (n=2342), drop duplicates (n=2326), remove whether it is a year< 2016 (n=1750), filter by title (n=119), select via abstract file(n=41), apply the quote rules(n=33), remove surveys (n=29), and remove similar (n=26). Using K-means clustering, LDA found trolls, SLR, CBOW methods apply on the Twitter dataset. The results are 89.7% have under 10 occurrences. Interesting result but are only a first step into understanding what reasonably high-level methods work to research and detecting malicious political content on Twitter. believe many things will be considered for the future with extrapolation in time, extrapolation in context. Within the future, through two distinct analyses, and are simultaneously very distinct from regular accounts [20].

Limitation

The drawbacks of the above work is that the dataset for contextual false information identification will easily become redundant as hyperlinks and social media tracks could no longer be retrievable at the time of publishing.

TABLE I

FAKE NEWS DETECTION ON SOCIAL MEDIA

Ref	Pre-processing	Method	Dataset	Results	Future Work
[1]	-Backward feature selection -Features extraction via important attributes	Deep neural models CNN SELU	twitter dataset	Extremely effective (92.7 percent ROC AUC)	In the future, adversarial approaches could shed light on the decision-making phase of the neural graph network, leading to improved interpretability of the model.

[2]	-Text cleanup -Stop words Removal -Tokenization -Labels were encoded using Label Encoder -transforming the texts into sequences and padding	LSTM BiLSTM model CNN GRU	Liar datasets Politifact dataset	0.326	Future areas of study include the exploitation of these relational functions along with graph neural networks, such as the newly created R-GCN.
[3]	-correlation-based feature selection	Implicit and explicit features analysis	BuzzFeed PolitiFact	As a result, specific people are most liked to regard fake news as actual news. These users show distinct characteristics than others that are most likely to believe the actual news.	In the future, the goal is to investigate other aspects of the user profile, like political bias and also user reputation, to better get whether these consumer traits can also use to spot false news.
[4]	-unwanted variable removed -article with fewer words and nobody's text is removed. -Multicolumn transformed into a single column. -Features extraction by using LIWC2015 tool. -Data scaling in the range of (0,1) -Data splitting with a ratio of 70/30	KNN XGBoost LR RF Perez-LSVM.	ISOT Fake News Dataset Kaggle	The maximum exactness obtained on ISOT False News Dataset is 99 percent, with the RF algorithm and also Perez-LSVM.	Graphic theory and machine learning methods may be used to recognize the primary outlets involved in the propagation of false news. Another potential future path might be like real-time false news recognition in videos.
[5]	-delete numbers from newsy data. -remove punctuation-mark words from newsy information. -Filter words that consist of character < N. -Apply case transfer to literal information. -delete stop words. -Stem newly information.	Bayes Net JRip SGD CVPS RFC LMT LWL Simple Cart Bagging Decision Tree KLR MLP ASC SMO CvC Ridor ZeroR Decision	ISOT Fake News Data set textual data BuzzFeed Political News Data set Random Political News Data set	The best mean values for accuracy, exactness, and F-Measurement were derived from the Decision Tree algorithm. .	More work set techniques and disparate function extraction techniques can also be unsegregated in the future to enhance the efficiency of the models.

		Stump			
[6]	-Feature extraction from social entities -PCA for intrinsic evaluation -predictions by examining specific test -fact-checking organization -record of correctly denying	Factual News Graph (FANG) SVM model on TF.IDF attribute CSI GCN	Stance-annotated dataset	0. 7518 0. 5525 0.6911 0. 7064	furthermore, strategy to applied multi-chore learning to jointly address the chore of misinformation news observation, source actuality prediction, and imitation chamber discovery.
[7]	-remove some meaningless statistical clues from the text. -debunking repository -linguistic-based features	LSTM GRU CNN Bert MVNN attRNN	Real-time dataset	0.864 0.857 0.851 0.867 0.805 0.852	Create and release a multi-modal data archive on Fake News on the Weibo Social Media (MCG-FNeWS) in the future to help assess the success of various methods by participants.
[8]	-Attentional learning based on text representation -Network representation learning based on heterogeneous graph neural network -Node features an aggregation -high-level features extraction	GCAL dEFEND and GCAL GNNs TCNN-URG	Politifact dataset Gossip cop dataset	.924 .828	In the future, using the news spreading path can be considered as the new type of link in the graph.

[9]	-Mathematical analysis -imitate using MATLAB on a 3-GHz Intel Xeon system running UBUNTU 19.2 LTS with 16-GB RAM. -delete undesirable words that will spread on the internet.	mathematical model	Real-world data	Obtained shows that if R0 is less than 1, then rumors and counterfeit information will be removed and OSNs will be locally stable. .	In the future, the approach of latent and separation will be used to avoid the dissemination of gossip on the social network and the spread of false news.
[10]	-analyze word patterns -statistical correlations of news articles -linguistic characteristics of news -using NLP models -training on a manually curated database	Adversarial Machine Learning Fakebox model	McIntire's dataset	The accuracy of McIntire's dataset is 52.77 percent, False rate is 31.79%.	In future work involves the creation of a visualized interface for news information graph crowdsourcing.
[11]	-Creator-Article Publishing Historical Records -Article Credibility Analysis with words content -Subject Credibility Analysis. -Creator Credibility Analysis	Gated Diffusive Unit(GDU).	PolitiFact dataset	GDU embraces several contributions from different sources simultaneously.	Besides, it is focused on similarities between news stories, creators, and news subjects.
[12]	-Text Sentiment Analysis -text-based rumor detection	LOGIT SVM-Linear Decision Trees Random Forest XG-Boost LSTM	PHEME labeled Twitter dataset	0.84 0.86 0.77 0.85 0.84 0.86	In the future, additional nostalgic sources derived from, for example, photographs, insert words in the picture, and other visual media, such as GIFs and clips, could improve model output and be considered.

[13]	- split into two subsets: preparation and research, with 70%-30%	ICS (Implicit Crowd Signals) Detective method	BuzzFeed PolitiFact	Accuracy = .9835 = .9791	The future work involves experiments with other measurement parameters, metrics, and databases, as well as exploring different methods of offering users an informed opinion on news and comparisons with techniques other than Crowd Signals.
[14]	-basic Python -Textblob structure utilizes to classify quotes; -Several quotations within a short -distance of each other within a document -quote attribution classifier	Bayesian machine learning system mixed-methods approach	locally generated dataset	The final average Accuracy Classifier is 0.69 and the overall Error Classifier is 0.31.	In the future, combing attribution feature extraction with other factors.
[15]	-Register Time (0.937): -Verified (0.099): -Political Bias (0.063): -Personality (0.036): -Status Count (0.035 -comparative analysis	explicit and implicit features	Politifact Gossipcop	P= 0.909 G= 0.966	In the future, analyze the correlations between suspicious accounts and false news to collectively detect malicious accounts and fake news products.

[16]	-removing the more frequent/active users -aggregating information -community features are combined with the textual features	SAFER (GNN) LR classifier	Gossipcop dataset PolitiFact	Results demonstrate that incorporating community-based modeling leads to substantially improved performance in this task as compared to the purely text-based framework	In future work, it would be fascinating to apply these techniques to other tasks, such as detecting rumors and modeling changes in public beliefs.
[17]	-raw information is modified by soaring -level conception by the use of concept hierarchies -consumption greatly -Given the large differences in total news consumption	list-based classification relied on prevalence	unique multimode dataset	Polarization is most appropriate to lie in the contents of ordinary reporting.	In the future, all possible origins of controversial material should consider potentially corrosive impacts on democracy.
[18]	-degree of compatibility between a personal experience -less effective on noisier datasets -Linguistic Cue -Network Analysis approaches,	Naïve Bayes Classifier Support Vector Machines Semantic Analysis	hyperplane dataset	help other researchers discover which combination of methods	In the future, evaluate the proposed Naïve Bayes Classifier, SVM, and Semantic Analysis process.
[19]	-Each generating news every epoch t. -Maximum spread at the next time step t +1 -Robustness against spammers	Detective Bayesian approach	Facebook dataset	The algorithm uses posterior sampling to deliberately pass off exploitation and discovery	In the future, it will also be necessary to perform user studies by deploying algorithms in the area-wide social framework.

[20]	-Remove I.P. and TJ (n=2773) -Remove missing DOIs (n=2342) -Delete duplicates (n=2326)) - Delete if year < 2016 (n=1750) -Filter by title (n=119) -clean by abstract (n=41) -Appling citation rules (n=33) -Remove Surveys (n=29) - Delete similar (n=26)	K-means clustering LDA found trolls SLR CBOW	Twitter dataset 118,816,838 total tweets	89.7% have under 10 occurrences	In the future, through two distinct analyses, and are simultaneously very distinct from regular accounts.

Fake news detection of COVID-19

Using a seven-stage context awareness (NLP) approach to health, psychosocial, and social problems emerging from the COVID19 pandemic sponsored social media [21]. Preprocessing is done by with tokenization, remove hashtags, and expand contractions, remove HTML tags, remove special characters, reduce repeated characters, art-of-Word identification, lemmatization, syntactic parsing, transformation and sorting, emotion score, and remove numeric words. NN, NNP, NNS, and NNPS, N-Gram chunking method, and POS chunking method applied on the Twitter dataset. Fake news more impact on health. Perform preprocessing operations requiring the implementation of language processing (NLP) techniques on 47,410,795 (over 47 million) data coronavirus-based responses from six social media sites – Twitter, YouTube, Facebook, Archinect.com, LiveScience.com, and PushSquare.com. Besides, 20 optimistic trends arose from our performance. In the future, initiatives will benefit states, health providers and organizations, institutions, etc., and separate in their efforts to reduce the spreading of COVID19 and mitigate its effects, furthermore in responding to any possible pandemics [21].

Developed the CNN model to test the performance of error detection algorithms [22]. Preprocessing is done by deleting the most frequent hashtags and list the ten most common claims. SVM, LR, RF, CNN, BiGRU, CSI, SAME/v, HAN methods are used to detect fake news linked to the Covid-19. Which more impact on human mentality CoAID contains 3,235 news, 294,692 user commitments, 851 social platform updates on COVID-19, and ground reality marks. 75% exactness, not a satisfactory score. So, the potential course of study is by a false news identification challenge over many state-of-the-art approaches [22].

Develop skip-gram model analysis on Instagram, Reddit, email, gab, and YouTube [23]. Investigate participation and concern in the COVID-19 theme and have a disparate measure of the disclosure of dialogue on a global plate for every forum and its client. Preprocessing is done by developing words inserted for the text corpus of each site, different word classes, and topics., assess the topics around, cluster words, and characterizes user's engagement. Methods are applied to the Reddit dataset, Instagram dataset, and Twitter dataset to detect fake news. Fit details on disease models that define fundamental replication numbers R0 on all social media networks. The results associated with the user interaction is accomplished using only the results of the API quest. Finally, have platform-dependent computational estimates of the amplification of rumors. In the future, it would help to create more productive disease frameworks for internet behavior and to introduce the most effective implementation techniques in times of crisis [23].

Here a basic NLP technique for identifying COVID-19 misinformation clips on YouTube using user opinion [24]. Using transfer learning pre-trained template to come up with a multi-label sorter that can classify artful material. Pre-processing is done with tokenization (only 1.95%), applied χ2 tests for every remaining word, multi-label classification on the ten samples, data splitting training (80%) test (20%), and removal of stop words. Finally, a display that appends the first hundred opinion as TD-IDF factor increases the clip's classifier validity by up to 89.4 percent. Ultimate research could grasp the clip's content to extend the classifier exactness. The detection of misinformation on the internet prevails an open challenge, and other research is required to grasp how the COVID19 miss infodemic spread to stop future ones [24].

Proposed BERT and GloVe method grow tools to flag COVID-19 related misinformation on the social platform, especially on social media like Twitter [25]. Pre-processing is done with vectorization and tokenization on a dataset of 6761 annotated tweets to gauge the success of misinformation identification systems on 86 different sections of COVID19 based fake news. Review current NLP frameworks in this data collection, provide initial benchmarks, and define primary issues to improve future models. For more work, pledge to constantly extend our annotated dataset by adding content from other domains such as news articles and Reddit, and myths from outlets outside Wikipedia [25].

Develop a dynamic deep learning framework for the analysis of false knowledge relevant to COVID19 [26]. Collect information to create a connect framework that utilizes a variety of DL strategies to identify misleading information. Use the Keras sequential model for identification. Improving the increased efficiency of the proposed assembly detection system. Preprocessing is done with feature engineering, remove noisy and unimportant content, delete repetitive info, delete halt words, delete every word of less duration, remove all links, and Remove empty samples. After that collecting the information, multiple EDA tasks were conducted to provide general acumen into the data. The findings obtained are encouraging and suggest the consistency and authenticity of the accurate information gathered for the production of deceptive information detection systems. In the future, add to the system's ability to manage data from other languages by operating on a hybrid system that suitable for both ML and DL strategies to develop a robust misinformation identification system [26].

Applied the basic NLP pre-processing method for the detection of fake information [27]. Pre-processing is done by with delete any unnecessary details from the data, removal of the short word, tokenization, and removing duplicates. For data cleaning, using the python library NLTK text blob and regular expression applied on the fake COVID-19 dataset. Finally, developed a machine learning classifier to detect misconceptions about COVID-19. Model earns an F1 score of 0.76 to discover incorrect level and also some other facts scan the papers. But lack of polyglots, another possibility to broaden the work is to build a knowledge graph for fact check news so that the machine can easily process the data to answer user queries [27].

CRT pre-processing is done with a score, utilizes LR robust standard mistakes, clustered on the participant's titles, and shares objectives for fake information detection [28]. Using the political twitter dataset for the performance. This resembles those previously uncovered for political counterfeit information, indicate that nudging persons to care related authenticity is an easy process to make smarter decisions on what to post on social media. After applying methods get the result of 80% accuracy. In the future, discover other titles and data (and misinformation) related to COVID-19 comes in ways other than title headlines [28].

Using widely available fact-checking tools, determine the reputation of the news reports being exchanged [29]. Through using a mixture of theoretical and realistic tools, you can also monitor the flow of disinformation in a snapshot of the Twitter ecosystem. Pre-processing is done by using the label propagation, semantic approach, and topological approach on the Twitter dataset. As a result, big exactness (AUROC up to 94 percent). In the future, assign polarization to the network nodes (users) and see the effect of low-quality knowledge producers and spreaders on the Twitter ecosystem [29].

Using FRED for trustworthy facts and medical misconceptions [30]. Investigate how justification in Explanation Logics DLs can spot differences linking trustworthy through medical and non-credible ones. Non-credible data is given in NL (e.g., "Covid-19 influence only the ancient "). Used the FRED converter to transform DLs automatically. Study on integrating both heavy machines: NL analysis and ontology logic aimed at signaling incorrect knowledge relevant to Covid-19. Apply on the CORD-19 dataset for the detection. In the future, occurring work incorporate (i) framework assessment and (ii) verbal reasons for every disagreement identified [30].

Limitation

The drawbacks of this work is that, due to the absence of polyglots, where only three languages are used for human annotated categories and the data is limited to the United States, it is also important to validate it elsewhere in the world.

TABLE 2

FAKE NEWS DETECTION OF COVID-19

Ref	Pre-processing	Methods	Datasets	Results	Future Work
[21]	-Tokenization -Remove hashtags -Expand contractions -Remove HTML tags -Remove special characters -Reduce repeated characters -art-of-speech tagging -lemmatization, syntactic parsing -transformation and filtering -sentiment scoring. -Remove numeric words	NN, NNP, NNS, and NNPS N-Gram chunking method POS chunking method	comments or posts from Twitter, Facebook, YouTube Complete number of comments at 8,021,341	20 positive themes emerged from the results	In the future, interference will help governments, fitness professionals and agencies, organizations, and separate in their efforts to reduce the shatter of COVID19 and mitigate its effects, as well as to respond to other potential pandemics.

[22]	-delete the most frequent hashtags -list ten most common claims	SVM LR RF CNN BiGRU CSI SAME/v HAN dEFEND	Covid-19 healthcare misinformation Dataset	0.3365 0.2871 0.3937 0.8126 0.2241 0.3576 0.7901 0.6824 0.7229	The future study leads through a false news identification challenge over a variety of state-of-the-art approaches.
[23]	-Create word embedding -for each platform's text corpus -separate groups of words and topics -assess the topics around -cluster words -characterize users engagement	Skip-gram model Partitioning Around Medoids (PAM) LDA LSA	Reddit dataset Instagram Dataset Twitter dataset	Finally, supply stage-depending on numerical estimates of whisper amplification.	In the future, it will relief to build the most effective disease framework for social behavior and to introduce the most productive communication techniques in times of catastrophe.
[24]	-Tokenization (only 1.95%) -applied $\chi 2$ tests for each remaining words -multi-label classification on the 10% sample -data splitting training (80%) and test (20%) -removal of stop words	LIWC NB XLNeT BERT RoBERTa logistic RL SVM and RF	YouTube comments dataset	increases accuracy from 82.2% to 89.4%.	Furthermore, the research could leverage the clip's content to improve the classifier accuracy.
[25]	-Vectorization -tokenization	GloVe NLI BEERT NLTK	COVIDLIES Dataset	Providing initial benchmarks and identifying key challenges	In the future, plan to continually extend our annotated dataset by adding content from other domains such as news articles and Reddit, and misconceptions from sources beyond Wikipedia.

[26]	-Feature Engineering -remove noisy and unimportant content. -remove repeated data -Delete stop terms. -Delete every word which width less Remove all links -Remove empty samples	DL algorithms GloVe Keras sequential model	COVID19 dataset	The findings obtained are promising and suggest the consistency and authenticity of the accurate information gathered for the production of deceptive information detection systems. Accuracy 99%	In the future, add to the system's ability to manage data from other languages by operating on a hybrid technique that deploys both ML and DL strategies to develop a robust misleading data identification technique.
[27]	-Remove unwanted information from the data -removal of the short word, -tokenization -Removing duplicates	NLTK regular expression Text blob	Fake Covid dataset	That framework achieves an F1 score of 0.7 to discover incorrect class and other facts search papers.	In the future, broaden the work is that build a knowledge graph for fact check news so that the machine can easily process the data to answer user queries.
[28]	-classification -utilize LR robust standard errors -clustered on member titles. -Expressing intentions 1 on the Likert 6-point scale	CRT	Political twitter dataset	80% accuracy	In the future, reports from other titles and data (and misleading) related to COVID-19 emerge in ways other than titles of headlines.
[29]	-use the label propagation -semantic approach -(topological approach	BiDCM fact-checking software	4.5M tweets in Italian language, from February 21st to April 20th, 2020	high exactness (AUROC up to 94 percent).	In the future, polarise the network nodes (users) and see the effect of low-quality knowledge creators and spreaders on the Twitter ecosystem.

[30]	-collect a corpus of common misconceptions -analyze this misconception -build evidence-based counter	FRED	CORD-19 dataset.	As a result, Automated translation of the Covid-19 myth to the FRED Logic Explanation	In the future, the Ongoing study includes (i) framework assessment and (ii) verbalizing explanations for each identified conflict.

Fake news detection of COVID-19 on Twitter

Proposed ensemble learning structure to check the integrity of a huge amount of data [31]. Preprocessing is done with raw data collection streaming API, performance assessment and comparison, normalization, and feature extraction. NBand BN models, KNN model, DT consisting mostly of C4.5 and RF models, and SVM are used for detecting covid19 disinformation in Twitter. Review of a broad data collection of tweets that have information on COVID19. The reaction gets with the proposed structure indicates high exactness in the identification of trustworthy and non-trustworthy tweets enclose COVID19 content. The average accuracy of 95.11 percent. In the future, we will search for revised ensemble approaches and machine-learning strategies to improve the existing model [31].

Inspect utilize an unsupervised ML method labeled the Biterm Theme Model (BTM), where classes of tweets accommodate the identical word correlated themes are grouped into theme clusters that contained discussions related to symptoms, research, and rehabilitation [32]. Preprocessing is done with sampling, tokenization (type v) and D (v, v0), removed hashtags, removed stop words, data cleaning, clusters, and removing duplicate tweets. Apply to the Twitter dataset that was compiled from the Twitter public API from 3 to 20 March 2020. As a result, a total of 3465 (<1 percent) tweets are reported, including consumer-produced discussions about the experiences of prospective users of COVID-19 symptoms and other disease experiences. Focus in the future on designing factor-based supervised ML classifiers depends on the defined discussion characteristics mentioned [32].

Use a Latent Dirichlet Allocation (LDA) based on a machine learning approach, identify common unigrams, bigrams, salient concepts, and themes, and thoughts in the tweets collected [33]. Preprocessing is done by with removed the hashtag symbol, removed non-English characters, removed special characters, removed punctuations, and stop-words, analyze unstructured text data. Apply on Twitter dataset (n=4,196,020). Analysis of the data through sentiment analysis and qualitative analysis. Finally, as a result, find, this confidence is no longer prominent as people tweet about reported incidents and deaths. Future research could investigate the dissemination of anti-Chinese/Asian feelings in social media and how people use social media networks to resist and oppose COVID-19 stigma [33].

Proposed a basic taxonomy to separate bot detection approaches into three classes: (1) social network knowledge systems; (2) crowd-sourcing and human intelligence leverage systems; (3) machine learning techniques focused on the discovery of highly predictive characteristics that distinguish between bots and humans [34]. Using ML methods for the discovery of fake news on the Twitter dataset. Preprocessing is done by deleting the usual n-grams of the online slang, removing hashtags, and n-gram extraction. The result observed how high bot score accounts use COVID-19 as a lever to improve the popularity of ideological hashtags that are usually correlated with lofty-rights in the united states. In the future, further examine the actions of the COVID-19 bots, to see if they are used purely for propaganda purposes, or whether other uses arise [34].

This model aims to use a series of features: TFIDF, word embeddings, statistical, and implicit features to completely benefit from the benefits of the features and improve overall performance [35]. Preprocessing is done with the tokenizer module, in addition to removing punctuations, numbers, and stop words, snowball stemmers, and feature extraction. Apply on the Twitter dataset for the performance. The judgment of all components is combined using a fusion formula. As long as the effects of the train collection of tasks are concerned, the combination model outperforms on each variable, which is equivalent to using just a group of features with its own best performing classifier. Besides, proposing a fusion component learning scheme could lead to more effective and better optimization of the weight parameters of the components are used [35].

Develop LDA using natural language processing [36]. Preprocessing is done by with drop URLs from tweets, tokenization, delete special characters, convert to lowercase, eliminate stop phrases, lemmatization, remove phrase sets, and uni-gram. Apply only English language tweets which collect through API credentials to produce a network diagram of related terms and words that could enhance visualization. After preprocessing, build a paper term matric of the subjects addressed in tweets relevant to mental wellbeing. Polarity measurement to classify neutral, positive, and negative elements of several of the points discussed. As a result, much of the tweets are linked to sorrow, horror, and the effect of COVID 19. In the future, attention can also be extended to other languages. Well, that allows us to better appreciate our emotions [36].

Applied multi-coder methods for fake news detection [37]. Using Clauset–Newman–Moore cluster algorithm & Harel–Koren fast multiscale layout algorithm on a Twitter dataset. Preprocessing is done by with identify the multidimensional communication activities, network analysis, content analysis. Comparatively explores how problems relevant to COVID-19 have been shared on Twitter via a network study. First, classified top news networks exchanged via tweets. Finally, a satisfying review of the information frames used in the high shared sources was carried out. The outcome of the network review indicates that the delivery of data in the coronavirus network was quicker than in the furthermore network, but two coders might not be adequate to guarantee reliability. More coders should be used to ensure the reliability of the study findings for further work in future studies [37].

Execute a remarkable upgrade of that TweetsKB dataset and also pipeline using the PDF method [38]. Preprocessing is done with a parallelized annotation pipeline, remove spam through an MNB classifier, sentiment analysis, harvesting, filtering, cleaning, connotation annotation, and metadata removal. The result, initiate several using cases from different regulations, currently using the corpus to gain notice and test computational approaches for different activities. For more work in the future, the extendable knowledge graph nature of the corpus can be used to phased incorporate additional contextual details [38].

Proposed an automated tool for identifying existing phase changes and comparing correlations over time in major issues around these countries [39]. Preprocessing is done by with tokenize (converting data to the smallest units) filtered unnecessary textual information by using existing Python tokenizer libraries referring to each particular language. LDA and PPL methods are used on the Twitter dataset to detect fake news examine the time gap between social media interest and reported patient count. As a consequence, an inverse relationship can be found between the number of tweets and actual diversity. In the future, theorize the issue attention cycle model on a global scale and see how it evolves in conjunction with local specific topics such as increasing or decreasing confirmed cases, government measures, and social conflicts [39].

Developed a BERT based machine learning classifier [40]. Preprocessing is done by normalizing texts, replacing account names, URLs, and emails, removing emojis, fast text skip-gram model for 5 epochs, the context window size of 5, n-gram size between 3 and 6, data splitting into a training (64%), development (16%), and test set (20%). To better understand the attention patterns on Twitter amidst the COVID-19 crisis. We developed a taxonomy of account categories and then proceed to annotate tens of thousands of accounts using Amazon Mechanical Turk. Apply on the Twitter dataset for the performance. The findings show that social media often offer a forum for analysts and elected officials to be widely understood throughout the global crisis. In the future, since within categories, the quality of specific messages and the alignment with the scientific consensus could vary [40].

Analyzed tweets that were tested using techniques common to social media analytics [41]. Preprocessing is done with tokenized using NLTK, Emoji package, and URLs are also removed using regular expressions. Using Linguistic Inquiry and Word Count (LIWC) method and Kullback Leibner divergence for Informativeness and Phrases (KLIP) apply to the Twitter dataset for the detect fake news. Results help us to recognize weaknesses in the available scientific coverage of the subject and to recommend measures to officials and social media users to tackle misinformation. In the future, the exploratory research that the authenticated Twitter account is often interested in generating or disseminating disinformation [41].

Analyzed the received tweets using single word rates (unigrams) and double terms (bigrams) [42]. The study leveraged the Latent Allocation of Dirichlet (LAD) for points modeling to classify the topics addressed in the tweets. The study also conducted sentiment analysis and derived the mean digit of retweets, shares, and followers for every topic, and measured the engagement rate for each topic. Preprocessing is done by removing non-English tweets, removing retweets, removing punctuation, stop word and nonprintable characters, normalizing Twitter user's mentions, and lemmatizing texts. The loftiest total of likes for tweets was 15.4 (economic mislaying), while the lowest was 394 (tour bans and caution). In potential research, the dissemination of "fake information" in the merger with contagious disease epidemic should be studied [42].

Proposed a framework using deep learning tools for characterizing twitter representatives based on an interpretation of the public graph extracted from the actions of the public network[43]. Pre-processing is done by content-based filtering, two parallel layers have been used for streaming., removed poorly connected nodes, and delete from the network in addition to the linked edges. Apply on the Twitter dataset for the detection performance. As a result, the topology of leaders' clusters, and this technique can be used for the monitoring of individuals. In the future, the foundation for a proactive application to inspire consumers with a positive effect on the mutual actions of the network [43].

Using Spread networks contain both retweets and conversation threads. Pre-processing is done by with collected the retweets using splitting, tokenization removed duplicate tweets, and textual content is also dropped to avoid redundancy [44]. As a result, news agencies find superiority among top users of Twitter and most shared URLs. ArCOV19 facilitates study in a variety of areas, including natural language analysis, knowledge retrieval, and social computing. In the future, the plan to continue gathering tweets for the near future, and the dataset is updated constantly with newly collected tweets and spread networks [44].

Using machine learning algorithms to simulate latent characteristics of apps, such as positions and policy instructions, utilize a dataset of 67 million tweets through 12 million consumers gathered within January 29, 2020, and 2020,4 March [45]. classify users root on their home nations, their social backgrounds, and their political ideology. Pre-processingis done by with tested the generalizability and re-trained it using the geotagged. As a result, achieve accuracies of 90.2% and 91.4%. Detect the fake news on Twitter related to COVID-19. A future study might be proposed automatically detecting new keyword monitoring in streaming data to dynamically shift collection and thereby catch further conversations as communication drifts between themes [45].

Current COVID-19 misleading information, a dynamically annotated deceptive dataset for COVID19 from Twitter [46]. The dataset was compiled over 36 days from 4 February to 10 March 2020. It is composed of 3,263M Arabic and also English tweets. Pre-processingis done with feature selection, feature extraction, removing the stop words, generalization, perform cleaning textual data, and remove rows text is empty. The tweets in the COVID-19 misleading information data set were explain using 13 disparate ML algorithms and using 7 disparate attribute extraction methods.TF, DT, KNN, LSVM, MNB, ERF, XGBoost, and GB methods are used. As a result, support researchers grasp the mechanisms behind the outbreak of COVID-19 on Twitter. For potential job directions, we might expand our suggested data collection to include information from related other languages such as French, Spanish, Chinese, etc [46].

Map a dashboard to tracking disinformation on the popular internet news distribution platform [47]. The control panel brings appearance to the social platform conversations surrounding the corona virus and the accuracy of knowledge posted on the site, renovate over time. Pre-processingis done by with a collection of streaming data using the Twitter API, the sentiment is aggregated, emerging policies, identify topics and trends, user activities, and coordination. The dashboard holds an ongoing archive of disinformation cascades, emotions, and emerging patterns over time, available online. As a result, it is critically important to detect and theoretically reduce the propagation of disinformation as near as possible to its point of origin. In the future, provide a source and social context-based identification of information derived from the network [47].

Develop the LIWC model, pre-processing techniques are done with normalized, identifying communities, data augmentation, test statistic, and bot detection [48]. The sociolinguistic analysis is used to detect liar information about covid-19 current methodology and analyses to describe the two overlapping online disinformation groups in COVID-19. Which are applied to the Twitter dataset for performance. These analyses show that disinformation groups are much more complicated, since they are heavily coordinated, and appear to be highly logical. The consequence is that the findings are statistically relevant ($p < 0.001$; $z = -6.23$). In future work, plan to investigate this interaction to establish a structured means of characterizing societies both in terms of disinformation and the diverse attitudes of users [48].

Presented a framework model stand on the universal sentence encoder to expose the key patterns of tweets in lately weeks [49]. A universal sentence encoder is known to extract semantic representation and resemblance of tweets. Pre-processingis done with sentence transformer, use clustering algorithms, text summarization, data extraction, and sentence embedding. Feed them to the K-means clustering algorithm to a set of related tweets (in a semantic sense). After that, a cluster description is collected utilizing a text summarization algorithm which is dependent on deep learning that can reveal the fundamental themes of all of the clusters. Apply on Twitter dataset between 2020-03-29 and 2020-0430 and TF-IDF, latent Dirichlet allocation LDA, BERT methods for detecting misleading information related to covid-19. As the result, the model can identify very insightful points by analyzing a huge number of sentence-level tweets. But for better performance, this model outperforms other common theme detection approaches [49].

Analyze the text messages that are related to Covid-19 [50]. Pre-processing is done by using AI and data analytics methods on all text messages. Using AI tools for analyzing each tweet analyses are divided into six categories. Apply state-of-the-art NLP templates for text, such as called object identification NER, part of speech marking PoS, the meaning of uncertainty, and classification. Use the most accurate well-known python tools and library for insuring the validation of the results. For future works, we want to work on a misinformation detection process of Covid-19 tweets that is one of the hot topics in the era of Covid-19[50].

Limitation

This study has limitations of the above work. Non-English Tweets are deleted from the analyses, and therefore the results are restricted to the consumer who is posted in the English language only.Only pattern a tendency of twenty hashtags as the key search names to collect the Twitter information. New hashtags keep appearing as the situation develops. Twitter users are not representative of the entire population globally, and Tweet patterns only indicate the views of online consumers about and react to COVID-19.

TABLE II

FAKE NEWS DETECTION OF COVID-19 ON TWITTER

Ref	Pre-processing	Methods	Datasets	Results	Future Work
[31]	-collecting the raw data Streaming API -performance evaluation and comparison -Normalization -Feature Extraction	C4.5 SVM KNN	Twitter dataset Full number of tweets received 980,100	95.11% 94.67% 94.39%	Look for upgrade ensemble approaches and ML strategies to improve the present paradigm in the future.
[32]	-Sampling -Tokenization (type v) and D(v, v0) -Removed hashtags -Removed stop words -data cleaning -clusters -Removing duplicate tweets	biterm topic model (BTM)	Twitter data (72,922,211)	A complete of 3465 (<1 percent) tweets were found, including consumer-generated discussions related to interactions associated with potential COVID19 symptoms and other disease experiences.	In the future, focused on developing factor-based supervised ML classifiers depend on identified exchanged characteristics reported.
[33]	-removed the hashtag symbol -removed non-English characters -removed special characters -removed punctuations, and stop-words -analyze unstructured text data	(LDA) using thematic analysis unsupervised machine learning approaches	Twitter dataset (n=4,196,020)	Finds, eventually this confidence is no longer popular as people tweet about reported cases and deaths	Future research may investigate the dissemination of anti-Chinese/Asian social sentiments. Media and how people use social media networks to resist and question the stigma of COVID-19

[34]	-remove common n-grams typical of online slang -removing hashtags -N-gram extraction	sophisticated machine learning	Twitter dataset 43.3M tweets	Observed how high bot score accounts use COVID19 as a lever to improve the popularity of ideological hashtags that are usually correlated with high-rights in the United States.	In the future, further examine the actions of the COVID19 bots, to see if they are used purely for propaganda purposes, or whether other uses arise.
[35]	-Tokenizer module -addition to eliminating punctuations, numbers, and stop words -Snowball stemmers -Feature Extraction	NLTK SVM with linear kernel Random forest TF-IDF features Embeddings Implicit+Explicit Combinational model	Twitter dataset	Mean Accuracy (EN)= 74.6 Mean Accuracy (ES)= 82.9	In the future, proposing a fusion component learning scheme could lead to a more efficient and better optimization of the weight parameters of the components used.
[36]	-Drop URL from tweets -Tokenization -Erase special character -Convert to lowercase -Delete stop words -Lemmatization -Delete group of words -Uni-gram	(LDA) uses Gibbs sampling method	Twitter dataset	The findings revealed that most of the tweets were linked to disappointment and anxiety and the effect of COVID 19.	In the future, attention can also be extended to other languages. well, that allows us to better appreciate the sentiment.
[37]	-identify the multidimensional communication activities -network analysis -content analysis	Node XL Clauset–Newman–Moore cluster algorithm	Twitter dataset	average 5.060, SD 2.904; N=40, P=.03, 95 percent CI 0.169-4.852	More coders should be used in future studies to ensure the reliability of the results of the study.

[38]	-parallelized annotation pipeline -remove spam through a MNB classifier -sentiment analysis -Harvesting, filtering, cleaning -Semantic annotation and metadata extraction.	RDF CNN	TweetsKB dataset TweetsCOV19	Corpus promotes web dialogue discovery and analysis even without expensive tweet feature computing.	In the future, classifying tweets or consumer-based on split URLs and statements cause disinformation to be identified.
[39]	-Tokenize (converting data to the smallest units) -filtered unnecessary textual information -utilize the real Python tokenizer libraries similar to every unique language	LDA PPL	Twitter dataset	Found an inverse correlation in the middle of tweet count and current diversity.	In the future, theorize the issue attention cycle model on a global scale and see how it evolves in conjunction with local specific topics such as increasing or decreasing confirmed cases, government measures, and social conflicts.
[40]	-Normalizing texts -Replacing account names, URLs, and emails -removing emojis -Fast Text skip-gram model for 5 epochs -context window size of 5 -n-gram size between 3 and 6. -Data splitting into a training (64%), development (16%), and test set (20%)	CAP BERT (bert-multilang)	Twitter dataset	Results demonstrate that the internet also offers a forum for analysts and elected officials to be extensively understood amid the economic crisis.	In the future, since within categories, the quality of specific messages and the alignment with the scientific consensus could vary.
[41]	-Tokenized using NLTK -Emoji package -URLs were also removed using regular expressions	Linguistic Inquiry and Word Count (LIWC) Method Kullback Leibner divergence for Informativenss and Phraseness (KLIP)	Twitter data (N=1500)	Results help us to recognize weaknesses in the available scientific coverage of the subject and to recommend measures to officials and social media users to tackle misinformation.	In the future, the exploratory research that the authenticated Twitter account is often interested in either producing or disseminating disinformation.

[42]	-Removing Non-English tweets -Removing retweets -Removing punctuation, stop word, and nonprintable character -Normalizing Twitter users mention -Lemmatizing texts	LDA	Twitter data n= 2,787,247	The uppermost total of likes for the tweets was 15.4 (economic loss), while the smallest was 3.94 (travel bans and warnings).	In potential research, the dissemination of "misleading data" in mixture with infectious disease breakout should be studied.
[43]	-content-based filtering -Two concurrent filters utilized for the streaming -removed poorly connected nodes -Delete from the network as well as the edges linked	Deep Learning tools	Twitter dataset 100.000 posts	The resultant topology of the leader clusters.	In the future, the base for a productive application to empower utilizer with a positive effect on the collective behavior of the network.
[44]	-collected the retweets using Pickaw -Tokenization -Removed duplicate tweets -textual content is also dropped to avoid redundancy	PHEME	Arabic Twitter dataset	Found the domination of news agencies among top consumers of Twitter and most shared URLs.	In the future, the plan to continue gathering tweets for the near future, and the dataset will be updated constantly with newly collected tweets and spread networks.
[45]	-tested the generalizability -re-trained it using the geotagged	machine-learning systems (locations and political orientations) prediction systems	67 million Twitter datasets	achieve accuracies of 90.2% and 91.4%	A future study might propose automatically detecting new keyword monitoring in streaming data to dynamically shift collection and thereby catch further conversations as communication drifts between themes.
[46]	-feature selection -feature extraction -Removing the Stop Words -Generalization -Perform cleaning textual data -Remove rows text is empty	TF DT KNN LSVM MNB ERF XGBoost GB	(Arabic/English) COVID-19 Twitter dataset	Support researchers consider the mechanisms behind the outbreak of COVID-19 on Twitter	For external candidates, directions might expand suggested data collection to include information from more languages like French, Spanish, Chinese, etc.

[47]	-collect streaming data using the Twitter API -sentiment is aggregated -emerging policies -identify topics and trends -User activities and coordination	Dashboard	Twitter dataset	As a result, it is highly important to detect and theoretically reduce the propagation of disinformation as near as possible to its point of origin.	In the future, will update research to provide the source and social context-based identification of information derived from the network.
[48]	-normalized -Identifying Communities -Data Augmentation -test statistic -Bot Detection -Sociolinguistic Analysis	Linguistic Inquiry and Word Count (LIWC)	Twitter dataset	find results to be statistically consequential ($p < 0.001$; $z = -6.23$).	In future work, plan to discuss this interaction to establish a structured means of characterizing cultures both in terms of disinformation and in terms of the diverse behaviors of users.
[49]	-Sentence Transformer -use clustering algorithms -text summarization -Data Extraction -Sentence Embedding	TF-IDF latent Dirichlet allocation (LDA). BERT	Twitter dataset between 2020-03-29 and 2020-0430,	The framework can identify very advantageous headlines by analyzing a huge number of sentence-level tweets.	In the future, this model outperforms other popular themes detection approaches
[50]	-using Flair version 0.5 -apply our state-of-the-art NLP -part-of-speech labeling (PoS) -sense disambiguation -Classification -used bigrams	LIWC LDA DeepMoji	Twitter dataset	results are showing the validity of that methods	For future works, we want to work on a misinformation detection process of Covid-19 tweets that is one of the hot topics in the era of Covid-19.

I. Discussion

Conclude our discussion by suggesting that the contextual characteristics of the Multiheaded self-attention process are well implemented than any other approaches we have addressed here. Utilizing transformer methods, further research will add features such as contextual characteristics of news stories, and also integrate photographs and videos to improve the output of counterfeit information detection systems. To increase the performance of the models, further work set techniques and various factor extraction techniques can also be implemented in the future. User studies would also need to be conducted by implementing algorithms in the area-wide social context. It could help to create more effective models for social activity and in times of trouble, to incorporate more active communication strategies. Suggested data collection may be extended to include data from several other languages around the World like Spanish, Chinese, French, etc. for external candidates' instructions.

II. CONCLUSIONS

In this work, the prevalence of false news and changes in technology in the last few years are discussed, which enable us to develop automatic frameworks and tools that help us to fight against misleading information or fake news. Besides, also the importance of fake news is explored. In COVID-19 the battle against fake news and uncertain information, hybrid models are needed. In this procedure, human wisdom is needed with digital tools. This study also compares the previously existing approaches used for the detection of fake news related to Covid-19. This is valuable information can convince researchers and participators to mark the issues and improve the current fake news detection system and establish the new one with more accuracy rates.

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