Fighting an Infodemic: COVID-19 Fake News Dataset

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Abstract
Along with COVID-19 pandemic we are also fighting an ‘infodemic’. Fake news and rumors are rampant on social media. Believing in rumors can cause significant harm. This is further exacerbated at the time of a pandemic. To tackle this, we curate and release a manually annotated dataset of 10,700 social media posts and articles of real and fake news on COVID-19. We benchmark the annotated dataset with four machine learning baselines - Decision Tree, Logistic Regression, Gradient Boost, and Support Vector Machine (SVM). We obtain the best performance of 93.46% F1-score with SVM. The data and code is available at: https://github.com/parthpatwa/covid19-fake-news-detection.

1 Introduction
The use of social media is increasing with the time. In 2020, there are over 3.6 billion users on social media, and by 2025, it is expected that there will be around 4.41 billion users (J.Cement, 2020). Social media has brought us many benefits like, faster and easier communication, brand promotions, customer feedback, etc; however, it also has several disadvantages, and one of the prominent ones being fake news. Fake news is unarguably a threat to the society (Panke, 2020) and it has become a challenging problem for social media users and researchers alike. Fake news on COVID-19 is a much bigger problem as it can influence people to take extreme measures by believing that the news is true. For example, a fake news (‘Alcohol is a cure for COVID-19’) led to many deaths and hospitalizations in Iran (Karimi and Gambrell, 2020). This shows how vulnerable we are to fake-news in these hard times and how severe the outcome can be, if we ignore them. The first step towards tackling the fake news is to identify it. We primarily restrict our investigation of the social media content to the topic COVID-19.

To tackle fake news, in this paper, we present a dataset of social media posts and articles on COVID-19 with real and fake labels. The targeted media platforms for the data collection are designated to be the ones that are actively used for social networking for peer communication and relaying information, which could be in the form of news, events, social phenomenon, etc. We collect both real news and fake claims that surfaced on social media on COVID-19 topic. Fake claims are collected from various fact-checking websites like Politifact1, NewsChecker2, Boomlive3, etc., and from tools like Google fact-check-explorer4 and IFCN chatbot5. Real news is collected from Twitter using verified twitter handles. We also perform exploratory data analysis and implement four machine learning baselines.

2 Related Work
There is no agreement amongst researchers over the definition of fake news. A simple definition of fake news is the news which is intentionally created false as news articles to mislead readers. It is adopted in various recent research (Mustafaraj and Metaxas, 2017; Potthast et al., 2018). In another definition, deceptive news which includes news fabrications, satire, hoaxes, etc., are considered as fake news (Balmas, 2014; Rubin et al., 2016). Despite

1http://www.politifact.com
2https://newschecker.in/
3www.boomlive.in
4https://toolbox.google.com/factcheck/explorer
5http://poy.nu/ifcnbot
| Label | Source | Text |
|-------|--------|------|
| Fake | Facebook | All hotels, restaurants, pubs etc will be closed till 15th Oct 2020 as per tourism minister of India. |
| Fake | Twitter | #Watch Italian Billionaire commits suicide by throwing himself from 20th Floor of his tower after his entire family was wiped out by #Coronavirus #Suicide has never been the way, may soul rest in peace May God deliver us all from this time |
| Fake | Fact checking | Scene from TV series viral as dead doctors in Italy due to COVID-19 |
| Fake | Twitter | It’s being reported that NC DHHS is telling hospitals that if they decide to do elective surgeries, they won’t be eligible to receive PPE from the state. The heavy hand of government. I hope Secretary Cohen will reverse course. #NCDHHS #COVID19NC #ncpol |
| Real | Twitter (WHO) | Almost 200 vaccines for #COVID19 are currently in clinical and pre-clinical testing. The history of vaccine development tells us that some will fail and some will succeed-@DrTedros #UNGA #UN75 |
| Real | Twitter (CDC) | Heart conditions like myocarditis are associated with some cases of #COVID19. Severe cardiac damage is rare but has occurred even in young healthy people. CDC is working to understand how COVID-19 affects the heart and other organs. |
| Real | Twitter (ICMR) | ICMR has approved 1000 #COVID19 testing labs all across India. There was only one government lab at the beginning of the year. #IndiaFightsCorona. #ICMRFightsCovid19 |

Table 1: Examples of real and fake news from the dataset. Fake news is collected from various sources. Real news is collected from verified twitter accounts.

the existence of several works dedicated for fake news, accurate automatic fake news detection is an extremely challenging task. The lack of a common acceptable benchmark dataset for this task is one of the key problems.

In 2017, Pomerleau and Rao organized the Fake News Challenge (FNC-1)\(^6\) task to address the issue. Authors proposed a new dataset using which both in-domain and cross-domain experiments are done with the help of machine learning and deep learning techniques to automatically detect fake news. Vlachos and Riedel (2014) collected 221 labeled claims that were fact checked by journalists available online. For this purpose, the fact checking blog of Channel45 and the Truth-O-Meter from PolitiFact is used. Zubiaga et al. (2016) presented a methodology to identify and annotate a dataset having 330 rumour threads (4,842 tweets) associated with 9 newsworthy events. The intuition is to understand how social media users spread, support, or deny rumours before and after its veracity status is resolved. In a similar way, several approaches have been developed to identify as-well-as limit the spread of (mis-)information (Acemoglu et al., 2010; Budak et al., 2011; Kwon et al., 2013; Ma et al., 2017; Nguyen et al., 2020; Chandra et al., 2020). Vo and Lee (2020) approach the problem of fake news spread prevention by proposing a multimodal attention network that learns to rank the fact-checking documents based on their relevancy.

For rumour debunking, Ferreira and Vlachos (2016) created a dataset named Emergent, which is derived from a digital journalism project. The dataset contains 300 rumoured claims and 2,595 associated news articles. This dataset is collected and annotated by journalists with an estimation of their veracity (true, false, or unverified) similar to fake news detection task. Researchers have also shown their interest in automatic detection of deceptive content for the domains such as consumer review websites, online advertising, online dating, etc. (Zhang and Guan, 2008; Warkentin et al., 2010; Shafqat et al., 2016; Long et al., 2017).

In addition to the above works, scientists have also been trying to discover AI related techniques to deal with ‘infodemic’ of misinformation related to the COVID-19 pandemic. Shahi and Nandini (2020) presented a multilingual cross-domain dataset of 5182 fact-checked news articles for COVID-19. They collected the articles from 92 different fact-checking website. Kar et al. (2020) proposed a BERT based model augmented with additional features extracted from Twitter to identify fake tweets related to COVID-19. They also used mBERT model for multiple Indic Language. Vijjali et al. (2020) developed an automated pipeline for COVID-19 fake news detection using fact checking algorithms and textual entailment.

3 Dataset Development

We curate a dataset of real and fake news on COVID-19:

\(^6\)http://www.fakenewschallenge.org
• **Real** - Tweets which are from verified sources and give useful information on COVID-19.

• **Fake** - Tweets, posts, articles which make claims and speculations about COVID-19 which are verified to be not true.

Table 1 gives some examples of real and fake news from the dataset.

### 3.1 Collection and Annotation

We follow a simple guideline during the data collection phase as follows:

- Content is related to the topic of COVID-19.
- Only textual English contents are considered. Non-English posts are skipped.

### 3.2 Fake News

We collect fake news data from public fact-verification websites and social media. The posts are manually verified with the original documents. Various web based resources like Facebook posts, tweets, a news piece, Instagram posts, public statements, press releases, or any other popular media content, are leveraged towards collecting fake news content. Besides these, popular fact-verification websites like PolitiFact, Snopes, Boomlive, etc, are also used as they play a crucial role towards collating the manually adjudicated details of the veracity of the claims becoming viral. These websites host COVID-19 and other generic topic related verdicts. The factually verified (fake) content can be easily found from such websites.

### 3.3 Real News

To collect potential real tweets, we first crawl tweets from official and verified twitter handles of the relevant sources using twitter API. The relevant sources are the official government accounts, medical institutes, news channels, etc. We collect tweets from 14 such sources, e.g., World Health Organization (WHO), Centers for Disease Control and Prevention (CDC), Covid India Seva, Indian Council of Medical Research (ICMR), etc. Each tweets is red by a human and is marked as real news if it contains useful information on COVID-19 such as numbers, dates, vaccine progress, government policies, hotspots, etc.

### 3.4 Dataset Statistics

From Table 2, we observe that, in general, real news are longer than fake news in terms of average number of words and characters per post. The vocabulary size (i.e., unique words) of the dataset is 37,505 with 5141 common words in both fake and real news.

The dataset is split into train (60%), validation (20%), test (20%). Table 3 shows the class-wise distribution of all data splits. The dataset is class-wise balanced as 52.34% of the samples consist of real news and 47.66% of the data consists of fake news. Moreover, we maintain the class-wise distribution across train, validation, and test splits.

We also analyse the dataset on token-level. The

| Attribute         | Fake  | Real  | Combined |
|-------------------|-------|-------|----------|
| Unique words      | 19728 | 22916 | 37503    |
| Avg words per post| 21.65 | 31.97 | 27.05    |
| Avg chars per post| 143.26| 218.37| 182.57   |

Table 2: Numeric features of the dataset
| Split   | Real  | Fake  | Total |
|---------|-------|-------|-------|
| Training| 3360  | 3060  | 6420  |
| Validation | 1120 | 1020  | 2140  |
| Test    | 1120  | 1020  | 2140  |
| Total   | 5600  | 5100  | 10700 |

Table 3: distribution of data across classes and splits. Note that the data is class-wise balanced and the class-wise distribution is similar across splits.

10 most frequent tokens after removing stopwords are:

- Fake: coronavirus, covid19, people, will, new, trump, says, video, vaccine, virus.
- Real: covid19, cases, new, tests, number, total, people, reported, confirmed, states.
- Combined: covid19, cases, coronavirus, new, people, tests, number, will, deaths, total.

Figures 1a, 1b and 1c show word clouds for fake news, real news, and combined data respectively. From the word clouds and most frequent words, we see that there is a significant overlap of important words across fake and real news.

4 Baselines and Results

**Pre-processing** - We remove all the links, non alphanumeric characters and English stop words.

**Feature extraction** - We use term frequency–inverse document frequency (tf-idf) for feature extraction. tf-idf for a word increases with its frequency in a document and decreases as the number of documents in the corpus that contain the word increases.

**ML Algorithms** - for classification, we experiment with Logistic Regression (LR), Support Vector Machine (SVM) with linear kernel, Decision Tree (DT) and Gradient Boost (GDBT). All algorithms are implemented using sklearn package. All experiments run in approx 1 minute on an i7 CPU. The code is available on github.8

Table 4 shows the results of ML models on validation dataset. The best F1 score of 93.46% is achieved by SVM closely followed by Logistic Regression (LR) with 92.75% F1-score. In comparison, Decision Tree (DT) and Gradient Boost (GDBT) reported significantly inferior performance with 85.25% and 86.82% F1-scores, respectively.

Figure 2 shows the confusion matrix of the predictions of SVM on validation set. Since we train, validate, and test the model on a balanced dataset, the predictions are also balanced across two labels.

5 Conclusion and Future Work

In this paper, we describe and release a fake news detection dataset containing 10,700 fake and real news related to COVID-19. We collect these posts from various social media and fact checking websites, and manually verify the veracity of each posts. We also benchmark the developed dataset using machine learning algorithm and project them as the potential baselines. Among the machine learning models, SVM-based classifier performs the best with 83.46% F1-score.

Future work could be targeted towards collecting more data, enriching the data by providing the reason for being real/fake along with the labels, collecting multilingual data. Using deep learning instead of machine learning is also worth exploring.

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8https://github.com/parthpatwa/covid19-fake-news-detection

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Table 4: Accuracy (Acc), weighted average Precision (P), weighted average Recall (P) and weighted average f1 score (f1) of ML models on validation data.

| Model   | Acc  | P   | R   | F1  |
|---------|------|-----|-----|-----|
| DT      | 85.23| 85.31| 85.23| 85.25|
| LR      | 92.76| 92.79| 92.76| 92.75|
| SVM     | 93.46| 93.48| 93.46| 93.46|
| GDBT    | 86.82| 87.08| 86.82| 86.82|

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Figure 2: Confusion matrix of SVM model in Validation data. Performance on both the classes is similar.
References

Daron Acemoglu, Asuman Ozdaglar, and Ali Parnechi. 2010. Spread of (mis)information in social networks. Games and Economic Behavior, 70(2):194 – 227.

Meital Balmas. 2014. When fake news becomes real: Combined exposure to multiple news sources and political attitudes of inefficacy, alienation, and cynicism. Communication Research, 41(3):430–454.

Ceren Budak, Divyakant Agrawal, and Amr El Abbadi. 2011. Limiting the spread of misinformation in social networks. In Proceedings of the 20th International Conference on World Wide Web, WWW ’11.

Shantanu Chandra, Pushkar Mishra, Helen Yanakoudakis, Madhav Nimishakavi, Marzieh Saeidi, and Ekaterina Shutova. 2020. Graph-based modeling of online communities for fake news detection. arXiv, 2008.06274.

William Ferreira and Andreas Vlachos. 2016. Emergent: a novel data-set for stance classification. In Proceedings of the 2016 Conference of NAACL.

J.Cement. 2020. Number of social media users 2025. Statista. Accessed: 2020-10-30.

Debanjana Kar, Mohit Bhardwaj, Suranjana Samanta, and Amar Prakash Azad. 2020. No rumours please! a multi-lingual-lingual approach for covid fake-tweet detection. arXiv, 2010.06906.

Nasser Karimi and Jon Gambrell. 2020. Hundreds die of poisoning in iran as fake news suggests methanol cure for virus. Times of Israel.

Sejeong Kwon, Meeyoung Cha, Kyomin Jung, Wei Chen, and Yajun Wang. 2013. Prominent features of rumor propagation in online social media. In Proceedings of the 13th IEEE International Conference on Data Mining (ICDM’2013).

Yunfei Long, Qin Lu, Rong Xiang, Minglei Li, and Chu-Ren Huang. 2017. Fake news detection through multi-perspective speaker profiles. In Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 2: Short Papers).

Jing Ma, Wei Gao, and Kam-Fai Wong. 2017. Detect rumors in microblog posts using propagation structure via kernel learning. In Proceedings of the 55th Annual Meeting of the ACL (Volume 1: Long Papers).

Eni Mustafaraj and Panagiotis Takis Metaxas. 2017. The fake news spreading plague: Was it preventable? In Proceedings of the 2017 ACM on Web Science Conference, WebSci ’17, page 235–239, New York, NY, USA. Association for Computing Machinery.

Van-Hoang Nguyen, Kazunari Sugiyama, Preslav Nakov, and Min-Yen Kan. 2020. Fang. Proceedings of the 29th ACM International Conference on Information and Knowledge Management.

Stefanie Panke. 2020. Social media and fake news. aace.

Martin Potthast, Johannes Kiesel, Kevin Reinartz, Janek Bevendorff, and Benno Stein. 2018. A stylistic inquiry into hyperpartisan and fake news. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 231–240, Melbourne, Australia. Association for Computational Linguistics.

Victoria Rubin, Niall Conroy, Yimin Chen, and Sarah Cornwell. 2016. Fake news or truth? using satirical cues to detect potentially misleading news. In Proceedings of the Second Workshop on Computational Approaches to Deception Detection, pages 7–17, San Diego, California. Association for Computational Linguistics.

Wafa Shafqat, Seunghun Lee, Sehrish Malik, and Hyun-chul Kim. 2016. The language of deceivers: Linguistic features of crowdfunding scams. In Proceedings of the 25th International Conference Companion on World Wide Web, WWW ’16 Companion, page 99–100, Republic and Canton of Geneva, CHE. International World Wide Web Conferences Steering Committee.

Gautam Shahi and Durgesh Nandini. 2020. Fakcovid – a multilingual cross-domain fact check news dataset for covid-19. ArXiv.

Rutvik Vijjali, Prathyush Potluri, Siddharth Kumar, and Tyagi Sundeep. 2020. Two stage transformer model for covid-19 fake news detection and fact checking. In Proceedings of the Workshop on NLP for Internet Freedom.

Andreas Vlachos and Sebastian Riedel. 2014. Fact checking: Task definition and dataset construction. In Workshop on Language Technologies and Computational Social Science, pages 18–22.

Nguyen Vo and Kyomin Lee. 2020. Where are the facts? searching for fact-checked information to alleviate the spread of fake news. arXiv, 2010.03159.

Darcy Warkentin, Michael Woodworth, Jeffrey T. Hancock, and Nicole Cormier. 2010. Warrants and deception in computer mediated communication. In Proceedings of the 2010 ACM Conference on Computer Supported Cooperative Work, CSCW ’10, page 9–12, New York, NY, USA. Association for Computing Machinery.

Linfeng Zhang and Yong Guan. 2008. Detecting click fraud in pay-per-click streams of online advertising networks. In Proceedings of the 2008 The 28th International Conference on Distributed Computing Systems, ICCDS ’08, page 77–84, USA. IEEE Computer Society.

Arkaitz Zubiaga, Maria Liakata, Rob Procter, Geraldine Wong Sak Ho, and Peter Tolmie. 2016. Analysing how people orient to and spread rumours in social media by looking at conversational threads. PLOS ONE, 11(3):e0150989.