No Rumours Please! A Multi-Indic-Lingual Approach for COVID Fake-Tweet Detection

Debanjana Kar*
Dept. of CSE
IIT Kharagpur, India
debanjana.kar@iitkgp.ac.in

Mohit Bhardwaj*
Dept. of CSE
IIT Delhi, India
mohit19014@iitd.ac.in

Suranjana Samanta
IBM Research
Bangalore, India
suransam@in.ibm.com

Amar Prakash Azad
IBM Research
Bangalore, India
amarazad@in.ibm.com

Abstract—The sudden widespread menace created by the present global pandemic COVID-19 has had an unprecedented effect on our lives. Man-kind is going through humongous fear and dependence on social media like never before. Fear inevitably leads to panic, speculations, and spread of misinformation. Many governments have taken measures to curb the spread of such misinformation for public well being. Besides global measures, to have effective outreach, systems for demographically local languages have an important role to play in this effort. Towards this, we propose an approach to detect fake news about COVID-19 early on from social media, such as tweets, for multiple Indic-Languages besides English. In addition, we also create an annotated dataset of Hindi and Bengali tweet for fake news detection. We propose a BERT based model augmented with additional relevant features extracted from Twitter to identify fake tweets. To expand our approach to multiple Indic languages, we resort to mBERT based model which is fine tuned over created dataset in Hindi and Bengali. We also propose a zero shot learning approach to alleviate the data scarcity issue for such low resource languages. Through rigorous experiments, we show that our approach reaches around 89% F-Score in fake tweet detection which supercedes the state-of-the-art (SOTA) results. Moreover, we establish the first benchmark for two Indic-Languages, Hindi and Bengali. Using our annotated data, our model achieves about 79% F-Score in Hindi and 81% F-Score for Bengali Tweets. Our zero shot model achieves about 81% F-Score in Hindi and 78% F-Score for Bengali Tweets without any annotated data, which clearly indicates the efficacy of our approach.

Index Terms—Fake tweet, multilingual BERT, Random Forest Classifier, social impact, COVID19

I. INTRODUCTION

With the insurgence of the most devastating pandemic of the century, COVID-19, the entire planet is going through an unprecedented set of challenges and hurdles. Every now and then new revelations surface either for COVID solutions e.g. medicines, vaccines, mask usage, or regarding COVID dangers. Along with factual information, it has been observed that large amounts of misinformation are circulating on social media platforms such as Twitter. The COVID-19 outbreak has affected our lives in a significant way. Not only does it pose a threat to the physical health of an individual, but rumors and fake facts can have an adverse effect on one’s mental well-being. Such misinformation can bring another set of challenges to governance if not detected in time especially due to it’s viral nature.

Veracity of rumours over social media makes the detection challenging, and has been studied widely in recent past [1], [2]. Though more popular or highly retweeted messages may seem to be factual, it need not be the case especially in fast dissemination periods such as the COVID era; Fig. 1 depicts an example. In addition, the proliferation of Twitter to diverse demography induces challenges due to usage of locality specific languages. For example, various Indic languages, e.g. Hindi, Bengali, Telugu, Kannada are widely used in Twitter. Though there are some datasets released in English [3] for COVID fake-news, there are hardly any datasets released for Indic-languages.

In this paper, we propose an approach where besides network and user related features, the text content of message is given high importance. In particular, we train our model to understand the textual content using mBERT [4] on COVID dataset to classify fake or genuine tweet. Our proposed work describes a method to detect fake and offensive tweets about COVID-19 using a rich feature set and a deep neural network classifier. We leverage Twitter dataset for fake news detection in English language released in [3]. Since today’s society is cosmopolitan and multi-lingual, we consider a language agnostic model to detect fake tweets. For fake detection in a multi-lingual environment we fine-tune mBERT (Multilingual BERT) [5] to obtain textual features from tweets. We created fake news dataset in two Indic-Languages (Hindi and Bengali) by extracting tweets and annotated them for misinformation. Our multilingual model achieves reasonably high accuracy

Fig. 1. Two examples of COVID-19 related tweets; Left one shows an example of fake tweet, which has high number of retweet and like counts; Right one shows an example of tweet with real facts, which is has low number of retweets. Number of retweets and likes is proportional to the popularity of a tweet.

https://github.com/google-research/bert/blob/master/multilingual.md

* Work done during internship at IBM Research, India.
to detect fake news in Indic-Languages when trained with combined dataset (English and Indic-Languages). Towards scalability and generalization to other Indic-Languages, we also propose a zero-shot approach where the model is trained on two languages, e.g. English with Hindi, and tested on a third language, e.g. Bengali. We experimented rigorously with various languages and dataset settings to understand the model performance. Our experimental results indicate comparable accuracy in zero shot setting as well. Belonging to the Indo-Aryan family of languages, the Indic languages share similar syntactic constructs which seems to aid the cross-lingual transfer learning and help attain good accuracy.

Our **key contributions** can be enumerated as follows:

i) We have created COVID-19 fake multilingual tweet dataset - *Indic-covidemic fake tweet dataset*, for Indic Languages (Hindi and Bengali), which is being released. As per our knowledge, this is the first multilingual COVID-19 tweet related dataset in Indic language.

ii) We propose an mBERT based model for Indic languages, namely Hindi and Bengali, for fake tweet detection. We show that the model, fine-tuned on our proposed multilingual dataset, outperforms single language models. Moreover, we establish benchmark results for Indic languages for COVID fake tweet detection.

iii) Our zero shot setting, suitable for low resource Indic languages, performs comparable to models trained with combined dataset on Indic languages. Our experimental evaluation indicates that feature representations are highly transferable across Indic Languages enabling extension to other Indic languages.

### II. RELATED LITERATURE

**Fake News Detection:** Fake news or false information involves various research streams such as fact-checking [5], topic credibility [6]. An overview of fake news detection approaches through data mining perspective on social media has been discussed in [1] and [7]. Various studies have also been carried out related to COVID-19 related disinformation. Identifying low-credibility information using data from social media is studied in [8], detecting prejudice in [9], related to ethical issues in [10], misinformation spread of socio-cultural issues in [11] and detecting misleading information and credibility of users who spread it in [12]. Some recent work have focussed on detecting fake news from Tweets. In GCAN [12], credibility of user is studied based on sequence of retweets using graph networks. On the other hand, SpotFake [13] uses multimodal information from tweet text, using BERT embeddings, and corresponding image to detect fake tweets. In HawksEye [14], textual and temporal information about retweets are leveraged. Our work differs from these as we train our model to identify fake news leveraging mainly text features supported by other user informations related to their credibility on Twitter.

BERT [4] has become a state-of-the-art as a contextual representation of various NLP tasks. mBERT, a multilingual variant, is pretrained on 104 languages which gained large popularity due to its exceedingly well performance in various cross-lingual NLP tasks [15] lately. In our models, we finetuned both BERT and mBERT on exiting and our created dataset for fakenews detection tasks.

**Covid-19 Datasets:** Recent surge in fake news detection research is also evident from various rumour detection datasets, such as, SemEval2019 task7 [16] to determine rumour veracity, SemEval 2019 task 8 [17] for fact-checking. Infodemic Covid-19 dataset [3] is one of the first tweet dataset to distinguish fake and negative tweets. Though most studies and dataset focusses only English language, it has become more important to study in other languages as well, in multilingual, especially with regard to COVID. In [18], COVID-19 Instagram dataset is developed for multilingual usage. In [3], besides English tweets, Arabic tweets have been also used to explore misinformation impact. However, there is no dataset available for fake tweet detection in Indic languages to the best of our knowledge. We are the first to create dataset for fake news in Twitter in two common Indic Languages, Hindi and Bengali, called as Indic-covidemic.

### III. DATA SET

*Indic-covidemic tweet dataset* is one of the first multilingual Indic language tweet dataset designed for the task of detecting fake tweets. We describe the details of the dataset in the following sub-sections.

1) **English Annotations:** In our work, the definition of fake tweets holds as follows: "Any tweet that doesn’t contain a verifiable claim is a malicious or fake tweet." For our task, we use the Infodemic Covid19 dataset [3] as one of the training dataset for our classifier. This dataset has 504 tweets in English and 218 tweets in Arabic, annotated with fine-grained labels related to disinformation about COVID-19. The labels answer seven different questions, which are related to negative effect and factual truthfulness of the tweet and we only consider the annotations for the first question, which is: "Does the tweet contain a verifiable factual claim?". For the interest of this task, we only utilize the English tweets of Infodemic Covid19 dataset.

2) **Indic Annotations:** In most of the existing tasks, detection of fake tweets have been predominantly done only in English. But in recent times, Twitter has seen a significant rise in regional language tweet. This formed our motivation to extend this task to Indic languages as well. For this task, the Indic languages of our choice are Hindi and Bengali. This choice is guided by the fact that these languages are the two most widely spoken languages in India and also the two most widely used Indic languages in the world. We now enlist the methods in which the Indic tweets were obtained and processed below.

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2Source: [https://tech.economictimes.indiatimes.com/news/internet/india-is-clocking-fastest-revenue-growth-for-twitter-india-md-manish-maheshwari/77099148](https://tech.economictimes.indiatimes.com/news/internet/india-is-clocking-fastest-revenue-growth-for-twitter-india-md-manish-maheshwari/77099148)

3Source: [https://en.wikipedia.org/wiki/List_of_languages_by_number_of_native Speakers_in_India](https://en.wikipedia.org/wiki/List_of_languages_by_number_of_native_Speakers_in_India)
We obtain the Bengali tweets from [19] which is a database of over 36,000 COVID related Bengali tweets, without any task-specific annotated labels. We randomly select 100 tweets from this database and annotate it with the same labeling schema followed by [3] for the first annotation question as mentioned above. We further augment the dataset with Bengali translations of the English tweets of the Infodemic dataset. We perform the translations using Google Translate API. Out of all the translations obtained we only keep those translations whose language is detected as Bengali by the same translation API.

For Hindi, we make use of the tweepy API [20] to scrape COVID related tweets from the Twitter interface. This was achieved by firing an API search with COVID related key-terms like "Covid", "Corona", etc. We follow the translation data augmentation process and the same labeling schema for Hindi tweets as well. Augmenting the dataset with machine translated texts adds noise to the dataset and helps in training a more robust model. The tweets in this dataset have been collected over a time period of March to May 2020 and records a balanced distribution of spam to non spam tweets which can be observed in the Tab. I.

| Language | Fake | Non-Fake |
|----------|------|----------|
| English  | 199  | 305      |
| Bengali  | 183  | 297      |
| Hindi    | 192  | 252      |
| Total    | 574  | 864      |

TABLE I

**INDIC MISINFORMATION DATASET STATISTICS**

We also consider the features extracted from the Twitter user information, as a part of the dataset. For English, we make use of the user features provided by [3]. For Bengali and Hindi we have scraped the user information using the tweepy API and have provided it along the dataset. We have made our dataset and codes publicly available to further the cause of research in this domain[3].

IV. PROPOSED APPROACH

Our proposed approach is built on top of the method used in [3]. The main essence of the proposed approach lies in the features used for classification task and the different classifiers and their corresponding adaptation done for identifying the fake tweets. The details are described below.

A. Extracted Features

We extract various textual and statistical information from the tweet text messages and user information separately, and analyse their role in the classification process. The different features are enlisted as follows:

1) **Text Features** (tweettext): We extract some of the twitter and textual features such as:
   i retweet_count - The number of times a tweet has been retweeted

2) **Twitter User Features** (tweetuser): "A man is known by the company he keeps." A considerable amount of literature in this task has already cited the immense importance of analysing the user’s persona by extracting features from the user’s Twitter profile. In our work, we extract the following 19 features from a user’s profile, out of which 7 features are new additions with respect to the work in [3]:
   i Chars_in_desc : The number of characters in user’s description.
   ii Chars_in_real_name : The number of characters in user’s real name.
   iii Chars_in_user_handle : The number of characters in user’s handle on twitter.
   iv Num_Matches (new): Number of character matches in real name and username.
   v Total_URLs_in_desc (new): Total number of URLs in user’s description.
   vi Official_URL_exists (new): Whether the user has an official URL or not.
   vii Followers_count: Number of people that are following the user.
   viii Friends_count: Number of people the user is following.
   ix Listed_count: Number of lists to which the user has been added.
   x Favourites_count: Total number of likes the user has received throughout the account life.
   xi Geo_enabled: Whether the user has allowed location access.
   xii Acc_life (new): Number of days since the account was created.
   xiii Verified: Whether the user account is verified officially by twitter or not.
   xiv Num_tweet: Total number of tweets tweeted by the user.
   xv Protected: Whether the user account is protected or not.
   xvi Posting_frequency (new): Number of tweets tweeted per day by the user.
   xvii Activity (new): Number of days since the user’s latest tweet.
   xviii Avg_likes_per_tweet (new): Total likes received by the user divided by total tweets tweeted by the user.
   xix Follower_friends_ratio: Followers’ to friends’ ratio.

3) **Fact verification score** (FactVer) - We use the tweet text as a search query in Google search engine and consider the search results from reliable sources only. For this, we have manually selected 50 websites as reliable, which consists of popular news websites. We get the FactVer score by taking the average of the Levenshtein distance between the tweet text and the titles obtained from the

[https://github.com/DebanjanaKar/Covid19_FakeNews_Detection]
4) **Bias score (Bias)** - An observed trait of fake tweets is that it often contains disturbing content which is malicious and in violation of Twitter’s terms of use [21]. A 2018 Amnesty International report shows women are abused on Twitter every 30 seconds, with racism, sexism and homophobia in the social media platform and usually such tweets contain untrue facts presented in a vindictive fashion. To explicitly make use of this knowledge, we use a Linear Support Vector Classifier (SVM) pre-trained on a very large annotated corpus. We use the pre-trained profanity checker to obtain the probability of a tweet containing offensive language and use it as the 'bias score' in our model. As can be observed in the feature map above Fig. 2, the 'bias score' obtained shows a strong negative correlation with the fakeness of the tweets.

5) **Source Tweet Embedding (TextEmb)**: The final and the most obvious feature in this task is the tweet itself. We consider the BERT/mBERT embeddings of the tweet text as the feature.

![Fig. 2. Correlation of hand-crafted features with the class-labels show the effectiveness of the extracted features for the classification task.](image)

The correlation plots of the hand-crafted features with the class-label is shown in Fig. 2. It can be observed that not all features are helpful for the classification task. Nevertheless for now, we have considered all the features together, and keep automatic feature selection as a future scope of work.

**B. Classifier**

Given a tweet, the above-mentioned features are extracted from it, various combinations of which are passed to the choice of classifier for the prediction task. The architecture of the proposed framework is shown in Fig. 3. We use different feature combinations and classifiers for our purpose. We use Linear Support Vector Machine (SVM), Random Forest Classifier (RFC), Multi Layer Perceptron (MLP) and in-built multilingual BERT (mBERT, base cased) classifier (FC layer + softmax) for the classification task. We fine-tune the mBERT classifier by appending a layer (768 times 2) at the end followed by softmax and tune it for the classification task. The parameter details of the classifiers can be found in the experimental section. We have experimented with various combinations of classifiers and features and the noteworthy ones have reported in the next section.

**V. EXPERIMENTAL DETAILS**

We perform out experimentation on detecting fake tweets on our proposed Indic-covidemic fake tweet dataset. The tweets are pre-processed, where the hashtags, URL, user-tags have been removed and the text is converted to lower case for uniformity. We first perform experimentation on English Tweets and extend it to suit the needs of the Indic tweets. The details are explained in the following sub-sections.

**A. English Tweet Classification - mono-Lingual classifier**

We started our experimentation by classifying the English tweets to either Fake or Non-Fake class. We use the BERT model with pre-trained weights to get the sentence embedding of the tweet texts. We used 80% of the dataset for training and 20% for testing. Pretrained BERT embeddings are being used with (or without) different feature combinations, to classify using Support Vector Machine (BERT_SVM) with linear kernel (C=1, Gamma=1), Random Forest Classifier (BERT_RFC) with 400 estimators, Multi-Layer Perceptron Neural Network (BERT_MLP) classifier. MLP uses 30 neurons in the first hidden layer and 10 neurons in second hidden layer, with ReLU activation function and trained for 1000 epochs during training. We also use mBERT embedding with top classifier layer (mBERT_NN) using FC layer (768x2) followed by softmax for classification purpose. Table II shows the performance
We observe that adding of features always does not improve the performance of the classifier. This is not strange while dealing with hand-crafted features. Most of the user features are correlated to the class-label. Hence it is expected that addition of user features will boost the classifier performance. However, due to the shortcomings of SVM and MLP in dealing with small sample size problem, we rely on the metric numbers obtained by RFC (offers a piece-wise linear decision boundary in the feature space) and Fine-tuned in-build mBERT classifier (mBERT_NN). We observe that TextEmb, tweetuser and FactVer are strong features and consider these for further analysis of Indic tweets. We emphasise on a high recall value as we want a low false positive value so that fake tweets gets filtered out to the best possible manner.

**B. Indic Tweet Classification - multi-Lingual classification**

We fine-tune mBERT and use text embedding (with and without FactVer) as features. We use fine-tuned mBERT for the classification task (mBERT_NN). Tab. II shows the performance of different experiments in multi-lingual settings. We also test each of the language tweets separately in a zero-shot settings, where one of the language tweets are being used only as the test set. As mentioned by Alam et. al. [3], transformers models are sensitive to the seed value specially when the training data is not very large. Following [3], we experiment with 20 different random seed and fix one particular seed for the entire experimentation.

**Analysis - TextEmb** is a strong feature which gives consistent performance in all the settings. This particular feature is tuned as per the FLayer (in-build classifier of mBERT) which further favours it. Addition of FactVer helps for Hindi, but not for Bengali tweets. However, we would like to conclude that it is a strong feature as well. It is to be noted, that the adaptation from English+Hindi to Bengali and English+Bengali to Hindi is encouraging. But when the classifier is tested on English tweets, while using Hindi+Bengali as train set, the performance deteriorates. This is due to the fact that the similarities between Hindi and Bengali is much more than Hindi-English or Bengali-English.

**C. Ablation Study**

We study the cases where our proposed method acts dubiously, which are as follows:

- Fake information from verified Twitter users - We have observed that the model gets confused in detecting false information when tweeted by a verified user. This can be overcome by considering similar examples during training, which will give less importance to the particular feature (verified) in tweetuser feature set.
- Adapting model for English tweets in zero-shot learning setting - As mentioned above, the model does not generalize when English is the test set and the model has been trained on Hindi and Bengali tweets. This is reflected in the last row of Tab. II. This is due to the immense linguistic difference of English with that of Hindi and Bengali. Since both Hindi and Bengali are Indo-Aryan languages, they are compatible with each other. This problem can be overcome by adding language specific layers in the architecture, which will take care of the linguistic features, specially in zero shot learning settings.
- Correlated features - Statistical classifiers do not always scale performance as the number of features increase, unlike deep neural networks. The hand-crafted features may seem intuitive at times, but may not always have the distinctive property to help in the classification task. We see this nature in our experiments as well.

We would like to emphasis that these gaps are mostly due to less number of training samples and inherent drawbacks in the classifiers that we have adapted for the task.

**D. API and Demo**

As a part of the project, we expose the model as a service through a flask API and static HTML page, where given the tweet id/text, it determines if the tweet is fake or not. Currently, this has been deployed in IBM intranet. It allows anybody to check if a given tweet is a fake one or not. Some of the API is shown in Fig. 4.

**VI. CONCLUDING REMARKS**

In this work, we propose a multilingual approach to detect fake news about COVID-19 from Twitter posts for multiple Indic-Languages. In addition, we also created an annotated dataset, Indic-covidemic tweet dataset, of Hindi and Bengali tweets for fake news detection. The proposed model is build on mBERT based embedding augmented with additional relevant features from Twitter to classify fake or genuine tweets. We
show that our model reaches around 89% F-score in fake news detection which supercedes SOTA scores for English dataset. We show that model trained with multiple Indic-Languages (our Indic-covid19 tweet dataset) fake news dataset tweets shows improved performance which can be attributed to cross-lingual transfer learning as many Indic-Languages share similar syntactic constructs. Moreover, we establish first benchmark for two Indic languages, Hindi and Bengali. Our model achieves about 79% F-Score in Hindi and 81% F-score for Bengali Tweets. Further, with the focus to scale our model for other low resource Indic-Languages, we have proposed zero-shot learning approach for fake tweet detection. Our zero shot model achieves about 81% accuracy in Hindi and 78% accuracy for Bengali Tweets without any annotated data, which clearly indicates the efficacy of our approach. In future, we would like to add an automatic feature selection module which can take the most informative subset of handcrafted features for the classification task.

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