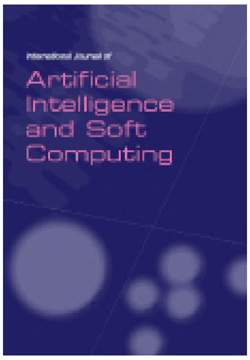

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CovFakeBot: a machine learning based chatbot using ensemble learning technique for COVID-19 fake news detection

Hunar Batra, Gunjan Kanwar Palawat, Kanika Gupta, Priadarshana, Supragya, Deepali Bajaj and Urmil Bharti*

Department of Computer Science,
Shaheed Rajguru College of Applied Sciences for Women,
University of Delhi,
Delhi, India
Email: i@hunarbatra.com
Email: palawatgunu@gmail.com
Email: kanikagupta232.kg@gmail.com
Email: priadarshanakuhu@gmail.com
Email: supragyasawarn22@gmail.com
Email: deepali.bajaj@rajguru.du.ac.in
Email: urmil.bharti@rajguru.du.ac.in
*Corresponding author

Abstract: The outbreak of the SARS-Cov-2 virus epidemic has been followed by a flood of misleading information on social media which is impacting millions of people every day. For this, we developed *CovFakeBot*, a conversational bot based on machine learning models to distinguish between fake and real news. The bot also provides the confidence score for the prediction that helps to ascertain trustworthiness of the news. Our system uses the COVID-19 tweet dataset and is trained over well-established state-of-the-art machine learning models. It is further optimised using ensemble learning methods for better accuracy. Results are evaluated using the accuracy and F1-score. We observed that ensemble learning using soft voting outperformed thus; we claim it as the best fit model. *CovFakeBot* is using WhatsApp Business API with Twilio to achieve conversational user interface. *CovFakeBot* will help the public to easily classify news as real or fake.

Keywords: COVID-19; fake news detection; ensemble learning; voting technique; Twilio sandbox; chatbot; soft voting classifier; natural language processing.

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Biographical notes: Hunar Batra is a graduate in Computer Science Honours from the University of Delhi. Her research interests are in the areas of deep learning, NLP, computer vision and one-shot learning. She has authored several national and international research publications.

Gunjan Kanwar Palawat is a graduate in Computer Science with honours from the University of Delhi. Her research interests include artificial intelligence, animation and game development.

Kanika Gupta is a graduate in Computer Science with honours from the University of Delhi. Her research interests are in the areas of front-end web development, machine learning and artificial intelligence.

Priadarshana is a graduate in Computer Science with honours from the University of Delhi. Her research interests lie in machine learning, artificial intelligence and data analytics as well as data science.

Supragya is a graduate in Computer Science with honours from the University of Delhi. Her research interests are in the areas of machine learning, artificial intelligence and networking.

Deepali Bajaj has over 15 years of teaching experience as an Associate Professor in the Department of Computer Science, Shaheed Rajguru College of Applied Sciences for Women (University of Delhi). She is currently doing her research in cloud and distributed computing. Her key research areas are microservices and function as a service (FaaS) of serverless technology. She has authored several national and international research publications.

Urmil Bharti has over 15 years of teaching experience as an Assistant Professor in the Department of Computer Science, Shaheed Rajguru College of Applied Sciences for women (University of Delhi). Earlier, she has more than ten years of industry experience. Her last designation was Senior Quality Analyst. Her research areas include cloud and distributed computing, serverless frameworks and machine learning. She has authored several national and international research publications.

1 Introduction

Coronavirus (COVID-19) is a virus that arose in China in December 2019 and has been labelled a Public Health Emergency of International Concern (PHEIC). Following the outbreak of COVID-19, there has been a plethora of literature published about disinformation. According to the findings, hostile content is rapidly changing and becoming more coherent. Fake news spreads far more quickly and easily than the virus itself. Therefore, detection of fake news has recently become an emerging research area that requires attention (Shu et al., 2017).

With technological advancements, social media is gaining traction because of its fast dissemination, low cost, and easy access (Shu et al., 2019). The younger generation prefers information to be received from the internet environment, thus social media platforms such as Facebook and Twitter, are widely used to disseminate news in various forms. Although this has advantages in terms of faster communication, social networks are also used to transmit a lot of misleading information. Countless information is being churned out every day on the internet and multiple social media platforms, impacting millions of people. Thus, fake news detection (Apuke and Omar, 2021) on social media is both crucial and technically difficult. WhatsApp is the most used messenger app for sharing and communicating information worldwide. According to WhatsApp 2022 User statistics report (Dean, 2022), WhatsApp had over two billion worldwide active users in India topping the list of having the most monthly active users of about 390.1 million.

Considering the above statistics, we developed the 'CovFakeBot', an ML based conversational bot that can predict the authenticity of COVID-19 tweets, by classifying them as 'real' or 'fake' for its users along with the accuracy of the prediction. The *CovFakeBot* not only helps people to know the real news and trust the source of information, but also assists in the prevention of spread of misleading information.

For this chatbot, we used a dataset namely 'fighting an infodemic: COVID-19 fake news dataset' to train five well-established machine learning models:

1 naïve-Bayes classifier

2 logistic regression classifier

3 Linear SVM classifier

4 SGD classifier

5 random forest classifier.

To achieve better predictive performance and model accuracy, we employed ensemble learning techniques (Dietterich, 2000) such as boosting – AdaBoost and XGBoost, bagging with logistic regression, decision tree, random forest and extra-trees classifier, and hard voting and soft voting. We observed that the soft voting approach outperformed other techniques and yielded the best results. Considering soft voting technique as the best fit model, we embedded it with Twilio Sandbox for WhatsApp which is a pre-configured environment. The contribution of this paper is three-fold:

1 Built a machine learning model by using five most popular algorithms. To enhance the accuracy of our model, ensemble learning techniques are applied.

2 Accuracy of model is determined by F1 accuracy metric.

3 Using above model, we developed *CovFakeBot* – a conversational user interface (CUI) is developed using WhatsApp Business API with Twilio to distinguish between COVID-19 fake and real news.

The remainder of this paper is laid out as follows: in Section 2, we review prior research studies in this subject. In Section 3, we discuss the dataset, techniques, and algorithms that we utilised to develop our application *CovFakeBot*. The outcomes of our studies are presented in Section 4. Section 5 discusses the implementation of *CovFakeBot*, Section 6 discusses the limitations and future work. Section 7 summarises our research our findings.

2 Related work

The topic of fake news detection has been a field of interest for researchers in recent times. A new list of important features is proposed for automatic detection of fake news. Authors have also evaluated the prediction performance of existing techniques for detecting false news. Their research shows that existing classifiers in combination with proposed features is valuable in detecting fake news (Reis et al., 2019).

A method for detecting fake news floating over social media networks was employed in a proposed approach (Aldwairi and Alwahedi, 2018). Their tool could identify and remove fake sites from search engines or social media news feed results. However, before using the tool, the user must first download and install it on their computer.

Machine learning approaches have become a successful strategy in the sphere of fake news detection and many researchers have been working on it. Few researchers applied a naïve Bayes method for fake news detection over twitter for various topics of 'natural phenomena' (Aphiwongsophon and Chongstitvatana, 2018).

The upsurge of COVID-19 pandemic has entailed a need for the research to be focused on news related to this disease. Now researchers have shifted their interest in classifying fake news just over COVID-19 related dataset. Another contribution to this field is the use of Naïve Bayes method for news classification over Facebook messenger messages (Nistor, 2021). Different supervised text classification algorithms on COVID-19 Fake news detection dataset are evaluated in one of the research article (Wani et al., 2021). The authors also observed the importance of unsupervised learning in the form of language model pre-training and distributed word representations. In another proposed approach, a transformer-based ensemble learning technique COVID-Twitter-BERT is used for fake news detection (Glazkova et al., 2021). Their experiments indicate that models based on BERT performed well in distinctive subject area.

Few researchers devised a two-step automated model using NLP for detecting COVID-19 fake news (Vijjali et al., 2020). Their first step finds out the most pertinent facts regarding user claims about COVID-19 and the second step validates truthiness in the claim based upon the true facts retrieved from a manually curated COVID-19 dataset. Unfortunately, this research work is only restricted to the dataset which they created irrespective of various news content which floats on social media. In our work, we trained and tested our model using a dataset which is a collection of tweets from various social media handles.

A heuristic-driven ensemble framework with a post-processing approach is used for detecting COVID-19 fake news (Das et al., 2021). Their approach considerably improved the system's fake tweet detection accuracy, but it works well only with tweets containing username handles or URL domains. In contrast to their research work, our *CovFakeBot* performs equally well even with tweets not having username handles or URL domains.

CoVerifi, a web application for COVID-19 news verification that combines the power of both the machine learning and human feedback to analyse the plausibility of news. It computes a credibility rating using machine learning models and other CoVerifi users' votes (Kolluri and Murthy, 2021). The problem with this approach is that hoax human feedback may adversely affect the outcome. In contrast, our *CovFakeBot* employs a well-trained machine learning model that accurately predicts the validity of COVID-19 tweets. A bidirectional encoder representations from transformers (BERT) approach is used to implement a new model for fake news detection (Heidari et al., 2021).

In our research work, we have proposed and implemented a system namely *CovFakeBot* that assists in COVID-19 related disinformation. It is a CUI system for assessing the trustworthiness of COVID-19 news. *CovFakeBot* is deployed over the selected ensemble learning model through the Flask web framework that uses the Twilio WhatsApp Business API to accept and process WhatsApp messages. *CovFakeBot* takes news as input from the user and displays their authenticity and accuracy percentage. *CovFakeBot* does not require any installation for its usage.

3 Methodology and model selection

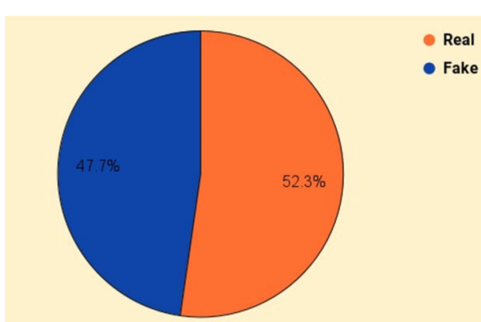
In this section, we will present the details of used dataset and steps of data pre-processing. Selection and application of different machine learning models are also discussed in depth.

3.1 Dataset and pre-processing

The dataset namely 'Fighting an infodemic: COVID-19 Fake news dataset', used in our research work is a collection of tweets related to COVID-19. The original dataset comprises 10,700 tweets with a vocabulary size of 37,505 and 5,141 unique words, and the dataset is also classified as real or fake. The data in this dataset is collected from actively accessed social networking sites used for relaying information and peer-communication. Real news is collected from twitter using verified twitter handles. Many fact-checking websites are used to assimilate fake claims. To name a few, referred website are NewsChecker, Politifact, and Boomlive. Few tools like Google-fact-check-explorer and IFCN chatbot are also used to collect fake news (Patwa et al., 2021). The original dataset was divided into three sets – training, testing and validation datasets. We combined the three sets of the original dataset and split it into two sets – training and testing for our models. The split ratio is 75:25 for training and testing datasets. The combined dataset is fairly balanced as the number of real news is approximately equivalent to the number of fake news (Kotsiantis et al., 2006), as shown in Figure 1.

Data pre-processing helps in converting raw data into an understandable format which can help in improving the accuracy of the result (García et al., 2016). We refined our dataset by removing URLs, hashtags, @ tags, symbols, pictograph, emoticons, transport symbols, map symbols, and whitespaces and then converted the tweet text into lowercase. We used the stemming technique for creating ngrams, using unigrams and bigrams (Jacovi et al., 2018). To process our data more efficiently, we used tokeniser to split our text and the simple bag-of-words (BoW) technique to create a feature vector and document term matrix. Further, Word2vec method was used to return a vector of zeros if the text is empty, with the same dimensionality as all the other vectors (Church, 2017).

Figure 1 Distribution of categorical data in the dataset (see online version for colours)



3.2 Model selection

In this subsection, we will briefly explain the state-of-the-art supervised machine learning models utilised in our research, followed by ensemble learning techniques. These techniques provide better performance, robustness, can help to minimise the variance of prediction and hence providing the high accuracy for classification.

3.2.1 Machine learning models

1. Naive Bayes: the naive Bayes algorithm is based on the Bayes theorem and assumes independence between every pair of characteristics. It is one of the most basic classification algorithms available, and it may be used for real-time detection, multi-class detection recommendation systems, and text classification or filtering (Rish et al., 2001).
2. Logistic regression: logistic regression is a supervised learning algorithm for classification used in machine learning. In this algorithm, the probabilities which describe the possible outcomes of a single trial are modelled with the help of a logistic function (Devi et al., 2017).
3. Linear SVM: linear support vector machine (SVM) is one of the most powerful machine learning algorithms. It is based on the concept of linear separability of data and mapping them in the given space based on which side of the gap they fall. It maximises the margin, called the optimal hyperplane and classifies the data (Devi et al., 2017).
4. Stochastic gradient descent (SGD): SGD is used to forecast model parameters that are compatible with the best match between actual and predicted outputs. It divides the observation set into small batches at random, computes the gradient for each mini batch, and moves the vector. Once all of the mini batches have been utilised, the iteration or epoch is complete, and the next one begins (Bottou, 2012).
5. Random forest: random forest is an ensemble learning technique in which classifier contains several decision trees on various subsets of the given dataset. It considers the average to enhance the predictive accuracy of that dataset. Instead of depending on a decision tree, it collects the predictions from each tree and forecasts the ultimate output based on the majority of prediction votes (Biau and Scornet, 2016).

3.2.2 Ensemble learning models

1. Hard voting: this is a voting classifier ensemble technique, in which the decision is made by taking into account the majority predictions made by each classifier (Dietterich, 2000).
2. Soft voting: this is the voting classifier ensemble technique, in which the decision is made by taking the average of the probabilities (or probability-like scores) and predicting the class label with the highest probability (Gandhi and Pandey, 2015).
3. AdaBoost: AdaBoost stands for adaptive boosting. It is a statistical classification meta-algorithm which is used in simultaneity with many other sorts of learning algorithms to boost up the performance. It works on the essence of learners growing

successively. It creates a set of weak learners by keeping a collection of weights over training data and adjusts them after each weak learning cycle adaptively. It then combines the multiple weak classifiers into one strong classifier.

4 XGBoost: XGBoost is a distributed gradient boosting framework that has been optimised for speed, portability, and efficiency. XGBoost performs well over small-to-medium structured or tabular data on classification and regression predictive modelling problems (Chen and Guestrin, 2016).

5 Bagging: bagging is the ensemble learning method that is used to achieve less variance within a noisy dataset. It is also known as bootstrap aggregation. In this approach, the samples are generated from a given dataset by randomly drawing the data points with replacement. Once the bootstrapped samples are created, these weak models are trained independently using regression or classification. Depending upon the algorithm used the average of all the predictions or the most voted class yield a more accurate estimate. In our work, we have used bagging with logistic regression, decision tree, random forest, and extra-trees classifier.

4 Result

In this Section, we present the metrics to ascertain the model accuracy. Performance results of individual machine learning and ensemble models are discussed in detail. The metrics and the results are used for model evaluation. Based on our results, we selected the best-fit model for *CovFakeBot*.

4.1 Performance evaluation metrics

Different evaluation metrics are used to measure the performance of various ML models. For classification problems, the confusion matrix is most widely used to evaluate the ML models. It is a matrix that represents the performance of a classification model on a test data set for which the true values are known. A 2×2 confusion matrix, associated with a classifier gives the predicted and actual classification. A confusion matrix for binary classification is given in Figure 2.

Terms associated with the confusion matrix are:

- *True positive (TP)* – the number of positive instances classified correctly.
- *False positive (FP)* – the number of positive instances which are misclassified.
- *True negative (TN)* – the number of negative instances classified correctly.
- *False negative (FN)* – the number of negative instances which are misclassified.

All the important performance metrics like accuracy, precision, recall, and F1-score (Batra et al., 2021) are based on confusion matrix. To evaluate the effectiveness of models, in our work, we used accuracy and F1-score metrics.

Accuracy: it is the measure of the fraction of correct predictions, which is described as:

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{1}$$

F1-score: this score is the harmonic mean of precision and recall values and is described as follows:

$$F1\text{-}score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \tag{2}$$

Figure 2 A confusion matrix for binary classification

Predicted Values \ Actual Values		
	True Positive	**False Positive**
	False Negative	**True Negative**

Source: Visa et al. (2011)

4.2 Performance evaluation of individual ML models

We have employed five different machine learning models to achieve the real v/s fake news classification and compared their performance over the test dataset. Performances of individual models are exhibited in Table 1. Our results show that linear SVM performed well on the test dataset and produced the best classification result with an accuracy of 92.24 and F1-score of 92.73.

Table 1 Accuracy and F1-score for individual machine learning models

S. no.	*ML model*	*Accuracy*	*F1-score*
1	Naive-Bayes	90.48	91.46
2	Logistic regression	89.81	90.36
3	Linear SVM	*92.24*	*92.73*
4	SGD	89.35	89.68
5	Random forest	89.86	90.08

Figure 3 Performance comparison of individual machine learning models (see online version for colours)

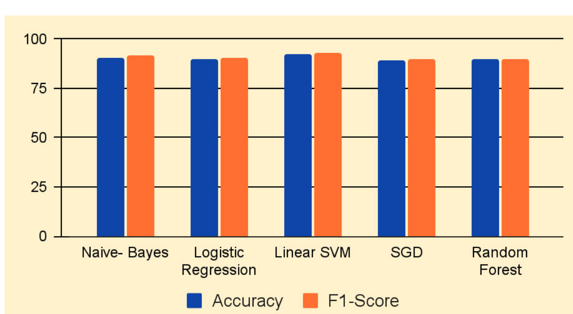


Figure 3 exhibits the performance of individual machine learning models, and we can discern that logistic regression, SGD and random forest had a tough competition among each other in terms of accuracy while linear SVM was marginally better than all other machine learning models.

4.3 Performance evaluation of ensemble models

We explored combinations of base models with various ensemble learning methods: voting, bagging and boosting. Using support vector classifier, decision tree, and logistic regression models, we employed both hard-and soft-voting techniques. Additionally, logistic regression, decision trees, random forests and extra tree classifiers were incorporated into the bagging classification process. For boosting, we utilised the XGB classifier and the adaptive boosting (AdaBoost) technique. Performances of ensemble techniques are shown in Table 2. We observed that the soft voting performed the best in comparison to other ensemble models over the test dataset with an accuracy of 94.57 and a F1-score of 94.05.

Table 2 Accuracy and F1-score for ensemble models

S. no.	*Ensemble model*	*Accuracy*	*F1-score*
1	Soft voting	*94.57*	*94.05*
2	Hard voting	91.99	91.08
3	Bagging using logistic regression	91.87	92.94
4	Bagging using decision tree	88.88	90.46
5	Bagging using random forest	90.25	91.49
6	Bagging using extra trees	91.53	92.53
7	AdaBoost	88.51	89.61
8	XGB	86.78	87.07

Figure 4 Performance comparison of ensemble models (see online version for colours)

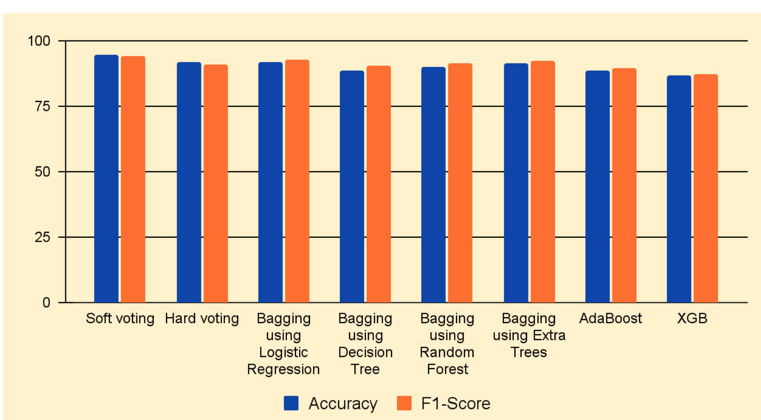


Figure 4 shows the performance of ensemble models. We observed that hard voting, bagging using logistic regression and extra trees performed well while XGB stood last, both in terms of accuracy as well as F1-score. Soft voting outperformed every other model in terms of both accuracy and F1-score.

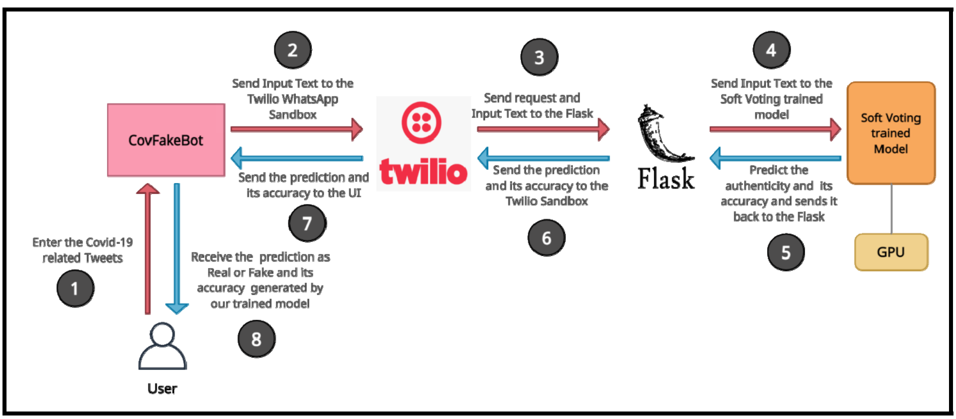
From our results, we concluded that soft voting has the highest accuracy in comparison to other ML models and thus it has been considered as the best fit model for our *CovFakeBot*.

5 Implementation

This section discusses the implementation and deployment of *CovFakeBot* in detail. *CovFakeBot* is a WhatsApp Chatbot built using Twilio API for WhatsApp and Flask framework for Python. Figure 5 shows the detailed architecture of *CovFakeBot*.

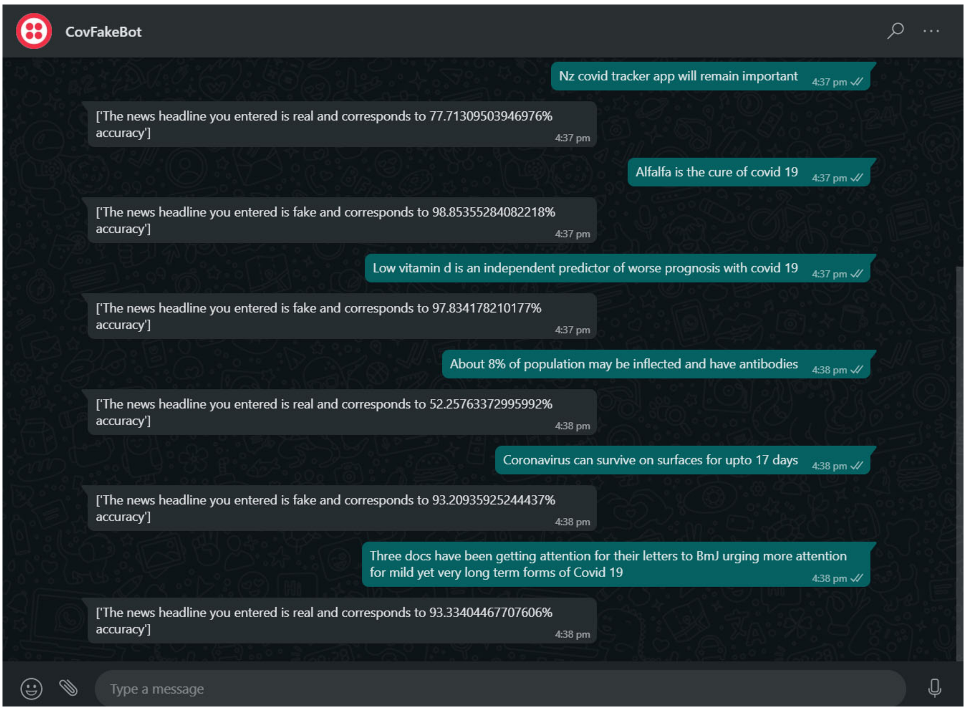
The pre-processing and training of the model is done in Google Colaboratory (Google Colab) graphic processing environment (GPU) (Carneiro et al., 2018), a cloud based Jupyter notebook environment. We used the NVIDIA Tesla T4 with 15 GB of RAM in our Colab's environment.

Figure 5 Detailed architecture of *CovFakeBot* (see online version for colours)



We deployed the soft voting model; our best fit model as discussed in the result section and connect it to the Twilio Sandbox for WhatsApp (https://www.twilio.com/docs/whatsapp/api) using the flask framework. Flask is a micro-web application framework written in Python programming language (Copperwaite and Leifer, 2015). It helps the end users to interact with our machine learning model directly from their respective web browsers without the need of libraries, protocol management, and code files. It generates an endpoint which can be accessed using Twilio WhatsApp Sandbox. The Flask application, implementing our trained model, needs to be visible from the web so that Twilio can send requests to it. Flask Ngrok Library (https://pypi.org/project/flask-ngrok/) is used to generate a public URL for the Flask application which is running in GPU so that Twilio can connect to it. Once Twilio is connected to our model, the WhatsApp Sandbox page provides us with a sandbox number assigned to our Twilio account and a join code. The join code begins with the word 'join', followed by a randomly generated two-word phrase. Our best fit model is now connected with the *CovFakeBot* and hence it is ready to use. Using the sandbox number and the join code assigned, the user can connect to the WhatsApp Sandbox and activate the *CovFakeBot* on their phone. Once the chatbot is activated, the user can then send the COVID-19 related news to check for their authenticity. The CUI of WhatsApp allows us to invoke a text chat by just a simple button click. The CUI of the *CovFakeBot* showing user input and its output, i.e., authenticity message along with the accuracy is shown in Figure 6.

Figure 6 CUI of the *CovFakeBot* (see online version for colours)



6 Limitations and future work

There are several validity threats to the design of this study. Since the model's development and deployment is done on moderate size dataset, so its performance needs to be validated on big datasets. The machine learning techniques are computationally intensive, but the experimental setup we used for our research work had limited resources. Moreover, there is no funding authority for this work, we confined our experiments to free software version of Google Colab whose RAM get exhausted easily, consequently leading to an increased compilation time. Large scale testing of this model is required to further validate our results.

To strengthen this model, other advanced and computational intelligence algorithms such as elephant herding optimisation (Li et al., 2020), monarch butterfly optimisation (Li et al., 2021b), dynamic learning evolution algorithm (Li et al., 2021a), GPT-3 (Bajaj et al., 2022) can be used to obtain predictions and check authenticity of news articles and reports.

In addition, *CovFakeBot* can be enhanced in future so that a user can also verify the authenticity of news, videos, and audios. The scope of the data on which *CovFakeBot* is trained can be augmented to other news disciplines apart from COVID-19. Thus, in long run, this research domain will be very beneficial in reducing the spread of fake information on sensitive issues.

7 Conclusions

The issue of fake news detection on social media is both challenging and relevant, so we have developed a CUI system *CovFakeBot* for identifying COVID-19 fake news. In our work, we evaluated and compared ten different machine learning and ensemble learning classifiers on a tweets' dataset. Based on our experimental results, we implemented the soft-voting model in our chatbot application. Use of this ensemble learning model drastically improved the fake tweet detection accuracy. *CovFakeBot* is developed and deployed using flask web framework, which accepts and processes user queries over the Twilio WhatsApp Business API. This chatbot interface accepts tweets from users and provides authenticity and accuracy percentage (credibility ratings) via soft voting.

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