SafeCampus: Multimodal-Based Campus-Wide Pandemic Forecasting

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The motivation of this work is to build a multimodal-based COVID-19 pandemic forecasting platform for a large-scale academic institution to minimize the impact of COVID-19 after resuming academic activities. The design of this multimodality work is steered by video, audio, and tweets. Before conducting COVID-19 prediction, we first trained diverse models, including traditional machine learning models (e.g., Naive Bayes, support vector machine, and TF-IDF) and deep learning models [e.g., long short-term memory (LSTM), MobileNetV2, and SSD], to extract meaningful information from video, audio, and tweets by 1) detecting and counting face masks, 2) detecting and counting cough for potential infected cases, and 3) conducting sentiment analysis based on COVID-19-related tweets. Finally, we fed the multimodal analysis results together with daily confirmed cases data and social distancing metrics into the LSTM model to predict the daily increase rate of confirmed cases for the next week. Important observations with supporting evidence are presented.

In light of rising concern about the COVID-19 pandemic, educational institutions have been temporarily closed to counteract the spread of the infection. To get students back on track, a multitude of K-12 and colleges reopened for in-person instruction. However, as many institutions reopened, the COVID-19 pandemic surged across the United States—as of October 22, 2021, around 45.3 million confirmed cases have been reported nationally, and more importantly, campuses are one of the most potential hotspots of COVID-19. Take the University of Alabama in Tuscaloosa as an example, where more than 1200 students and 166 employees have tested positive in the two weeks since the fall semester began for in-person learning. In this situation, educational institutions are struggling with the difficult decision of how to welcome students back to campus during the COVID-19 pandemic.

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To assist K-12 and colleges around the world to face the balance between minimizing the impact of COVID-19 on the learning outcomes while maintaining the safety and well-being of campus stakeholders (e.g., students, staff, and faculty, as well as visitors), we propose SafeCampus, a multimodal-based campus-wide COVID-19 pandemic forecasting platform based on the pervasive video, audio, and tweets, which can help thoughtful planning for not only the administration but also campus stakeholders. Note that the proposed techniques can be applied, adjusted, and customized for any campus. We chose Wayne State University (WSU) as our case study to present our approaches.

PANDEMIC FORECASTING AND 3-D CHOROPLETH MAP

In this work, the COVID-19 pandemic forecasting refers to the daily increasing rate of COVID-19 confirmed cases for the next week. With the development of public WiFi/5G and the prevalence of the surveillance camera in campus buildings, we envision that a timely 3-D choropleth map that indicates different pandemic increasing rates based on Google Earth will be enabled, as shown in Figure 1, which uses the

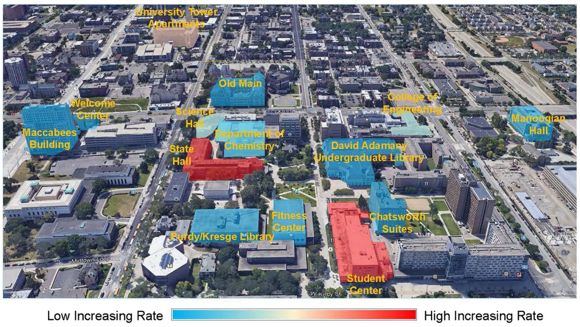

FIGURE 1. Exemplar visualization of the COVID-19 case increasing rate for the next week at the WSU campus.

gradient color (from blue to red) to reflect the low to high predicted case increasing rates for the next week on the building level. If the predicted increasing rate is greater than or equal to 1, the corresponding location will be highlighted by the red color. Since Google Maps does not have an open-source API that can automatically obtain the boundaries of buildings, we manually labeled building areas based on WSU's satellite image from Google Earth, and Figure 1 serves as a visualization result for a campus-level in this work. In the future, considering a border application environment, manual labeling might lead to high labor costs; in this case, researchers can leverage instance segmentation methods (such as BlendMask) to train models to automatically obtain building boundaries. Then, based on the prediction results and location information, a 3-D choropleth map, such as Figure 1, can be obtained.

MOTIVATION OF MULTIMODAL-BASED PREDICTION

The multimodal-based prediction is mainly driven by three reasons.

1) *Video*: It is well known that wearing a face mask can help to prevent the spread of COVID-19 disease and contain the number of casualties. Ananthanarayanan *et al.*[1] pointed out that cameras are pervasively deployed, e.g., around a single camera installed for every 29 people on average, which indicates that it is feasible to use the pervasive video captured by campus cameras for face mask detection.
2) *Twitter*: The pandemic situation is mainly reported by hospitals with a large delay, which is not conducive to the rapid detection of the epidemic situation; while social media (such as Twitter) data are closer to real time. Twitter users can share their experiences (including physical conditions) at will. Previous work proves that Twitter data may imply clues to the outbreak of COVID-19.[2]
3) *Audio*: The work of Imran *et al.*[3] studied possible infection of COVID-19 by cough detection. However, cough is also a symptom of non-COVID-19-related diseases. This makes the diagnosis of COVID-19 infection through cough alone very challenging. In this article, we only regard cough detection as a preliminary screening approach and combine it with video and tweets data to do COVID-19 pandemic forecasting.

KEY EXPERIMENTS, LIMITATIONS, AND SIMULATIONS

Specifically, we first trained three models to extract meaningful information from video, audio, and tweets by 1) detecting and counting face masks, 2) detecting and counting cough for potential infected cases, and 3) conducting sentiment analysis based on COVID-19-related tweets with the goal of classifying tweets according to the sentiment that is expressed as positive, negative, or neutral. Finally, we fed the multimodal analysis results together with *daily confirmed cases data* and *social distancing metrics* into the long short-term memory (LSTM) model for prediction, i.e., the case increase rate for the next week. Due to the data limitations, i.e., the population is still limited in the campus currently, we conducted simulation experiments to show the effectiveness of the prediction. The details of simulation experiments will be introduced in the "COVID-19 Pandemic Forecasting" section.

CONTRIBUTIONS

The core innovation of our study is in providing actionable insights on the real-time multimodal analytic technologies for the analysis and fusion of COVID-19-related information from video, audio, and tweets information. Specific contributions are listed as follows.

- Detect face masks and count the number of people with masks in the real time.
- Detect cough voices and identify potential COVID-19 infected cases.
- Conduct tweet sentiment analysis to classify tweets based on their sentiments, such as positive, negative, or neutral.
- Predict the COVID-19 case increasing rate for the next week by undertaking a multimodality approach.

BACKGROUND AND RELATED WORK

Audio Analysis and COVID-19

Before the pandemic, some works were introduced to recognize cough sounds, and the related tests have been conducted at homes and apartments, but the amount of this type of research is limited. For example, researchers at the Massachusetts Institute of Technology have now discovered that the asymptomatic people of COVID-19 may cough differently from healthy individuals.[4] These differences are not decipherable by the human ear, but it turns out that they can be recognized by machine-learning models.

Tweet Analysis and COVID-19

As an important social media open-source data, mining useful information from Twitter is a research hotspot. During the pandemic, more and more researchers are focusing on tweet analysis on worldwide COVID-19 outbreaks. For example, Manguri *et al.*[5] have pulled out Twitter data using the Tweepy and TextBlob library in Python based on two specified hashtag keywords, i.e., "COVID-19" and "coronavirus," and applied sentiment analysis on the collected data. Similar studies[2,6-8] have also been conducted.

Video Analysis and COVID-19

Compared to traditional object detection, face detection adds more features related to faces to improve accuracy. However, wearing a mask almost makes traditional face detection and recognition technology ineffective in many situations, such as community access control and facial security checks. Therefore, there is an urgent need to improve the existing face recognition technology for masked human faces. During the pandemic, early studies about face mask detection[9,10] have been proposed, which motivate later research work.

MULTIMODAL DATASET SELECTION

Regarding audio, tweets, and video analysis, we select different datasets to train diverse models with the goal of 1) detecting and counting face masks, 2) detecting and counting cough for potential infected cases, and 3) conducting text sentiment analysis. Then, as to the pandemic forecasting, we add two other datasets, i.e., COVID-19 daily cases dataset and social distancing dataset. The detailed data description is listed as follows.

Audio Dataset

We collected coughing audio data from the "Cough Dataset" from Kaggle. It includes heavy coughing and shallow coughing due to COVID-19. The dataset consists of 12,377 coughing samples with a total length of 238 minutes.

Twitter Dataset

The "COVID-19 Tweets Dataset" was collected starting from July 25, 2020, and published on Kaggle, which contains more than 170,000 COVID-19 tweets with text. These tweets are collected using Twitter API and a Python script. We also collected Sentiment140 dataset. It contains 1,600,000 tweets with text, which was extracted using the Twitter API. The tweets have been annotated and they can be used to detect sentiment.

Video Dataset

"Wider Face" and the "MAsked FAces (MAFA)" datasets are both typical public datasets supporting face mask detection. Wider Face contains 32,203 images with 393,703 normal faces with various illumination, pose, occlusion, etc. MAFA contains 30,811 images and 34,806 masked faces, but some faces are masked by hands or other objects instead of physical masks. We also collected another video/images dataset containing multiple subjects (with/without mask) walking within a university environment, and this environment could better help us to achieve our research goal, i.e., face mask detection on the campus-level.

COVID-19 Daily Cases Dataset

We also obtained and analyzed the daily cases data from Michigan's official Coronavirus dashboard, including the number of confirmed cases and the number of reported deaths.

Social Distancing Dataset

We also collected and analyzed the social distancing-related attributes for Wayne County and Michigan State from the COVID-19 Impact Analysis Platform published by the University of Maryland.

MULTIMODAL-BASED ANALYSIS AND RESULTS

In this section, we present the methods and results of 1) audio-based cough detection, 2) tweet sentiment analysis, and 3) video-based face mask detection. In this work, we adopt Intel Fog Reference Design (FRD) as the experimental platform. FRD is equipped with a powerful Intel Xeon E3-1275 v5 CPU containing four

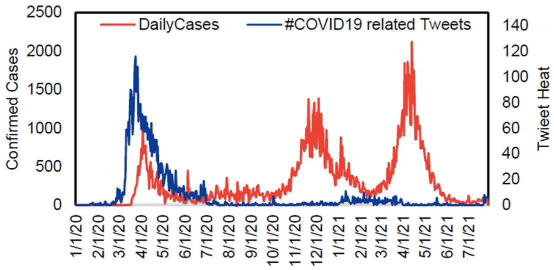

FIGURE 2. Changes in the number of COVID-19-related tweets and confirmed cases.

cores. The memory of FRD is 32 GB and the operating system installed is Ubuntu 16.04.6 LTS.

Text-Based Tweet Analysis

Changes of COVID-19-Related Tweet Heats Over One and a Half Year

We first collect the latest tweets covering one-and-a-half years (timestamp: January 1, 2020–July 29, 2021) through keywords from Twitter to analyze the change in the number of COVID-19-related tweet data and compare it with the change in the daily cases. The keywords are related to COVID-19 (e.g., "corona" and "coronavirus") and vaccines (e.g., "delta," "vaccinated," "Pfizer," "Moderna," and "Johnson"). We selected all extractable historical data within a 15-mile radius of WSU. Figure 2 presents the changes in the number of COVID-19-related tweets and daily confirmed cases.

Tweet Sentiment Analysis

Adopted methods: We then employed three models, i.e., Naive Bayes, support vector machine (SVM), and TF-IDF, for tweet sentiment analysis. Naive Bayes model is an extremely fast and simple classification algorithm that is often suitable for very high-dimensional datasets. An SVM is a supervised machine learning model that uses classification algorithms for two-group classification problems. TF-IDF[11] is a technique for text vectorization. The TF-IDF value increases proportionally to the number of times a word appears in the document and is offset by the number of documents in the corpus that contain the word, which helps to adjust for the fact that some words appear more frequently in general.

Sentiment analysis results: Figure 3(a) presents the sentiment analysis results of COVID-19-related tweets. We compared Naive Bayes, SVM, and TF-IDF. We use three different evaluation metrics, including Acc, Macro Avg, and Weighted Avg, to compare the sentiment classification ability. Weighted Avg is the abbreviation of weighted average, and the formula is $\bar{x} = \frac{1}{n}\sum_{i=1}^{k} x_i f_i$, where i is the index of different numbers. Macro Avg is short for macroaveraged F1 score, which is suitable for multiclassification. Here, $\text{Macro\_Avg} = \frac{1}{N}\sum_{i=0}^{N} \text{F1-score}_i$, where i is the class index and N refers to the number of classes.

Simulation Groups

Then, we divide five groups of tweet datasets to simulate different level of COVID-19 situations (buildings) and evaluate the ability of TF-IDF to analyze the sentiment of COVID-19-related tweets.

Specifically, the generated five datasets are mixed by two open-source tweet datasets, i.e., COVID-19 Tweets Dataset and Sentiment140 Data, which were combined in different proportions to simulate five campus buildings with different COVID-19 tweet heat levels. Each group has 60,000 tweets in total. For example, in Group1, there are 10,000 COVID-19-related tweets, whereas Group2 includes 20,000 COVID-19-related tweets. Similarly, Group5 has 50,000 COVID-19-related tweets. Table 1 shows the sentiment analysis results of each tweet group, where all tweets are first filtered by COVID-19-related hashtags and then classified into three sentiments: positive, negative, and neutral with TF-IDF algorithm analysis.

Audio-Based Cough Detection

Adopted Approaches

As for the detection model, we adopted one traditional machine learning model (SVM) and two deep learning models (MobilenetV2 and LSTM-deep). MobilenetV2 has a limited size of network weights and computing amount, making it popular for embedded applications. LSTM-deep[12] is a new version of LSTM-based model and specially developed for cough detection.

Simulation Experiments and Results

The model was first trained over a dataset consisting of 19,808 pieces of sound slices, including the same number of records, including coughs and other types of audio data. Then, we evaluated model performance over five groups of unseen test datasets, each of which has 2502 samples with the positive ratio (e.g., the coughing percentage) of 0.1, 0.2, 0.3, 0.4, and 0.5, to simulate different hotspots of COVID-19.

The evaluation results are shown in Figure 3(b). We can observe that the accuracy of the Mobilenetv2 outperforms the others and shows better potential for embedded applications as it is light weight and costs less computing power; LSTM has a higher false-negative rate and becomes less reliable; and the SVM can

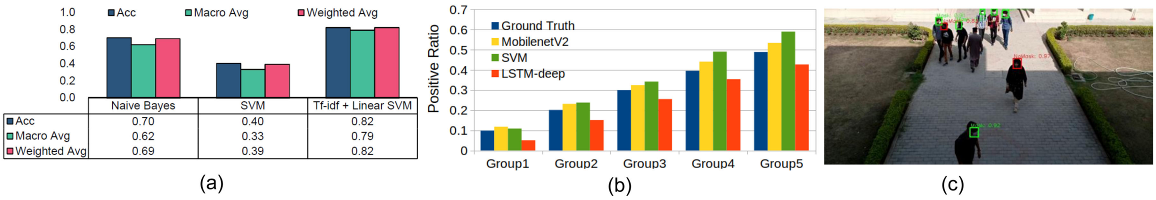

FIGURE 3. Experiment results of audio, tweet, and video analysis. (a) Tweets sentiment analysis. (b) Cough detection. (c) Face mask detection.

be considered as a baseline, being widely used in the detection of specific sound with lower accuracy than MobilenetV2.

Video-Based Face Mask Detection

Problem Statement and Adopted Models

We then formulated the problem of face mask detection as a traditional object detection problem followed by a binary classification. Specifically, we first used SSD to detect faces since SSD shows superior spatial feature extraction capability and has less computation cost. Then, we conducted binary classification based on the detected face results to output the face mask detection results.

Methodology and Detection Results

In this work, we chose a face mask dataset for training and testing purposes. We randomly took 80% of the datasets for training and the rest for validation. We used some commonly used measure, i.e., accuracy, to evaluate the performance of face detection. Our experimental results presented a promising detection accuracy, i.e., achieving around 0.90 of face detection accuracy while achieving 0.88 of accuracy on face mask detection. Figure 3(c) shows an example of the face mask detection results. Green boxes highlight the detected faces with masks, whereas red boxes represent the faces without masks.

Data Processing

The COVID-19 prediction for a specific building requires answering questions about the source of information (such as video, audio, Twitter, and the number of confirmed cases) on the building level. At present, Twitter and cough data cannot be specific to each building, and for some buildings, we cannot get the COVID-19-related data for a whole day, either. Therefore, our processing method is as follows: Twitter and cough data are collected on the district/block level, and we take 1) the number of local coughs/per thousand people, 2) the number of Twitter/per thousand people, and 3) their analysis results as the context data for all buildings. Then, the mask-wearing ratio and average social distance data can be obtained through cameras deployed on campus to provide related and individual information for each building. Besides, the daily case information can also be specific to each building. Therefore, we can feed the aforementioned information into the model to obtain the epidemic forecasting for each building.

TABLE 1. Results of tweet sentiment analysis.

	Group1	Group2	Group3	Group4	Group5
Positive	3975	7812	11,606	15,350	19,198
Negative	1420	3185	4847	6509	8099
Neutral	4605	9003	13,547	18,141	22,703

COVID-19 PANDEMIC FORECASTING

In this section, we aim to predict the daily increasing rate of confirmed cases for the next week by combining video, audio, and tweets information. In addition, since previous work presented that daily social distancing information is helpful to predict the number of confirmed cases,[13] we also collected social distancing-related data for Wayne County from the COVID-19 Impact Analysis Dataset. It includes various attributes contributing to social distancing, e.g., the percentage of people staying at home and the average number of all trips taken per person.

Problem Solution

Brief Model Intuitions

In this work, we carried out LSTM networks,[14] which is motivated by the reason that LSTM includes a memory cell that tends to preserve information for a relatively longer time, and a gating mechanism that allows deciding what should be kept in the memory cell, and how the new input data contribute to what is already in the memory cell. Hence, LSTM is effective for sequential data modeling and uncovering long-term temporal connections.

TABLE 2. Evaluation for nine experiment groups.

Group	D	D+C	D+T	D+SD	C+T+SD (A-D)	D+C+T (A-SD)	D+C+SD (A-T)	D+T+SD (A-C)	D+C+T+SD (A)
RMSE	0.0103	0.0094	0.0258	0.0131	0.0115	0.0109	0.0139	0.01382	**0.0085**
MAE	0.0076	0.0075	0.0103	0.0075	0.0086	0.0063	0.0086	0.0084	**0.0058**

The boldface values in Table 2 indicate the lowest RMSE and MAE respectively, which represents the highest accuracy among nine experiment groups.

Training Methodology and Model Descriptions

We used fivefold cross-validation, which is a validation technique to judge how models perform to an unseen dataset and also avoid overfitting. Specifically, there are two LSTM layers connected to two fully connected (dense) layers. A single LSTM layer has 128 kernels, and the dense layer has 64 kernels. In the second LSTM layer, the dropout value is set to 0.25 so it can disconnect with the neurons in the later layers and, therefore, reduce the possibility of overfitting. Finally, we empirically set the same learning rate of 0.001 for LSTM, and the drop-out rate was determined to be 0.25.

Input Attributes and Data Limitations

In general, there are three types of data used to train the prediction mode, including 1) daily COVID-19-related data, such as confirmed cases, 2) social distancing-related metrics, and 3) daily multimodal analysis results from video, audio, and tweets, including a) daily mask-wearing rate obtained by campus video analysis, b) daily cough numbers based on the audio collected by mobile phone application with users' permission, and c) daily COVID-19-related tweets that are obtained by the tweet analysis.

Note that although we trained a model to detect cough in "Multimodal-Based Analysis and Results" section, currently we do not have the chance to collect real-world voice of WSU since we are still developing mobile applications for the audio analysis. Therefore, we design practical, reasonable, and alternative methods to simulate the campus cough detection results. More specifically, considering that it takes an average of five days from being infected to be diagnosed as confirmed cases,[15] i.e., there are five days before the disease was confirmed, and patients begin to show related symptoms, such as cough. Therefore, we assume that the number of existing patients on day t is the number of people who cough on the day of $t-5$. In this way, we get the number of coughs and use it as one input attribute to train the prediction model.

Effective Measurements

We used root-mean-squared error (RMSE) and mean absolute error (MAE) to evaluate the prediction quality of the LSTM model. RMSE is the arithmetic square root of the mean square error, and MAE measures the average magnitude of the errors in a set of predictions. The smaller the value of RMSE or MAE, the better the accuracy of the prediction model.

Experiment Groups

To show the impact of tweet analysis results (T), cough detection results (C), daily cases data (D), and social distancing related data (SD) on the prediction of daily increasing rate, we conducted experiments on nine experimental groups. Our first step was to combine all categories of features to train models using LSTM methods, and we labeled this group as A group (A representing "All"). Then, we excluded all cough detection results but kept the features that were left, and we denoted it as A-C group. After deleting tweet analysis results, we got A-T group. Similarly, we got A-SD group and A-D group. In addition, in order to figure out the impacts of daily cases data, cough detection results, tweet analysis results, and social distancing related data, we also got D, D+C, D+T, and D+SD group (see Table 2). There are 434 pieces of training data in total covering from January 1, 2020, to March 10, 2021, and we set 80% of them as a training dataset and the rest 20% as the validation dataset to train models, respectively.

Prediction Results and Discussions

The key prediction quality measures for the nine experiment groups are as follows.

1) Regarding experiment results, we observed that A group performs the best across all experiment groups, i.e., achieving lowest MAE (0.0058) and RMSE (0.0085), which shows the capabilities of LSTM in predicting COVID-19 daily increasing rate for the next week. This observation verifies our hypothesis that all the considered data are both useful and helpful for improving the effectiveness of confirmed-cases prediction.
2) Considering the difference of the MAE and RMSE score between A group and other groups, we observed that A-T group, A-C group, A-SD

group, and A-D group achieve the larger RMSE and MAE score than A group, i.e., there is the effectiveness degradation between A group and A-T group, as well as between A group and other groups. This observation proves that tweet, cough, social distance, and daily cases analysis results are both critical for the improvement of confirmed-cases prediction.

3) As can be seen in Table 2, the prediction results based on only daily cases (D group) can achieve a reasonable performance (0.0103 of RMSE and 0.0076 of MAE), and its performance can be effectively improved when cough data are fed (D+C group) into the model. However, if only adding Twitter data (D+T group) and social distancing data (D+SD group), the performance improvement may not be achieved. For example, only adding social distance data (D+SD group), the related RMSE and MAE values are both higher than D group, indicating a worse prediction performance. This observation may indicate that a) coughing is a more useful indicator of COVID-19 prediction compared with only adding Twitter data and social distancing data in our experiments; and b) due to the limited amount of data collected on a daily basis, feeding new features may bring about the negative impact on the model performance (such as overfitting or learning abnormal features of sample data).

CONCLUSIONS

In short, to assist the administrations of K-12 and college campuses to make the thoughtful plans to reopen, we first trained three multimodal-based models to detect face masks, cough voices, and identify whether the social media posts with the location marks are related to COVID-19 for a large-scale college campus based on pervasive audio, video, and social media information. In addition, we trained a deep learning model to predict the daily increasing rate so that we can further identify the potential COVID-19 outbreak in campus buildings with location marks. Next, we aim to create a web service that could visualize the prediction results for campus stakeholders to aid in preventing the spread of COVID-19 and protect campus safety.

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REFERENCES

1. G. Ananthanarayanan *et al.*, “Real-time video analytics: The killer app for edge computing,” *Computer*, vol. 50, no. 10, pp. 58–67, 2017, doi: 10.1109/MC.2017.3641638.
2. J. Li, “Twitter sentiment analysis during COVID-19 in Florida,” Ph.D. dissertation, College Arts Sci. Inst. Artif. Intell., Univ. Georgia, Athens, GA, USA, 2020. [Online]. Available: https://www.proquest.com/docview/2479729261?pq-origsite=gscholar&fromopenview=true
3. A. Imran *et al.*, “AI4COVID-19: AI enabled preliminary diagnosis for COVID-19 from cough samples via an app,” *Informat. Med. Unlocked*, vol. 20, 2020, Art. no. 100378, doi: 10.1016/j.imu.2020.100378.
4. J. Laguarta, F. Hueto, and B. Subirana, “COVID-19 artificial intelligence diagnosis using only cough recordings,” *IEEE Open J. Eng. Med. Biol.*, vol. 1, pp. 275–281, Sep. 29, 2020, doi: 10.1109/OJEMB.2020.3026928.
5. K. H. Manguri, R. N. Ramadhan, and P. R. M. Amin, “Twitter sentiment analysis on worldwide COVID-19 outbreaks,” *Kurdistan J. Appl. Res.*, vol. 5, pp. 54–65, 2020, doi: 10.24017/covid.8.
6. X. Zhang, H. Saleh, E. M. Younis, R. Sahal, and A. A. Ali, “Predicting coronavirus pandemic in real-time using machine learning and big data streaming system,” *Complexity*, vol. 2020, pp. 1–10, 2020, doi: 10.1155/2020/6688912.
7. Y. Li *et al.*, “Constructing and communicating COVID-19 stigma on Twitter: A content analysis of tweets during the early stage of the COVID-19 outbreak,” *Int. J. Environ. Res. Public Health*, vol. 17, no. 18, 2020, Art. no. 6847, doi: 10.3390/ijerph17186847.
8. K.-C. Yang, C. Torres-Lugo, and F. Menczer, “Prevalence of low-credibility information on twitter during the COVID-19 outbreak,” in *Proc. ICWSM Workshops*, 2020, doi: 10.36190/2020.16.
9. M. Loey, G. Manogaran, M. H. N. Taha, and N. E. M. Khalifa, “A hybrid deep transfer learning model with machine learning methods for face mask detection in the era of the COVID-19 pandemic,” *Measurement*, vol. 167, 2021, Art. no. 108288, doi: 10.1016/j.measurement.2020.108288.
10. X. Kong *et al.*, “Real-time mask identification for COVID-19: An edge computing-based deep learning framework,” *IEEE Internet Things J.*, vol. 8, no. 21, pp. 15929–15938, Nov. 2021, doi: 10.1109/JIOT.2021.3051844.
11. S. M. H. Dadgar, M. S. Araghi, and M. M. Farahani, “A novel text mining approach based on TF-IDF and support vector machine for news classification,” in *Proc. IEEE Int. Conf. Eng. Technol.*, 2016, pp. 112–116, doi: 10.1109/ICETECH.2016.7569223.

12. N. Simou, N. Stefanakis, and P. Zervas, "A universal system for cough detection in domestic acoustic environments," in *Proc. 28th Eur. Signal Process. Conf.*, 2021, pp. 111–115, doi: 10.23919/Eusipco47968.2020.9287659.
13. Y. Yao, T. G. Geara, and W. Shi, "Impact of COVID-19 on city-scale transportation and safety: An early experience from Detroit," *Smart Health*, vol. 22, 2020, Art. no. 100218, doi: 10.1016/j.smhl.2021.100218.
14. S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, 1997, doi: 10.1162/neco.1997.9.8.1735.
15. N. M. Linton *et al.*, "Incubation period and other epidemiological characteristics of 2019 novel coronavirus infections with right truncation: A statistical analysis of publicly available case data," *J. Clin. Med.*, vol. 9, no. 2, 2020, Art. no. 538, doi: 10.3390/jcm9020538.

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