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An integrated fog and Artificial Intelligence smart health framework to predict and prevent COVID-19

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ABSTRACT

Nowadays, COVID-19 is spreading at a rapid rate in almost all the continents of the world. It has already affected many people who are further spreading it day by day. Hence, it is the most essential to alert nearby people to be aware of it due to its communicable behavior. Till May 2020, no vaccine is available for the treatment of this COVID-19, but the existing technologies can be used to minimize its effect. Cloud/fog computing could be used to monitor and control this rapidly spreading infection in a cost-effective and time-saving manner. To strengthen COVID-19 patient prediction, Artificial Intelligence(AI) can be integrated with cloud/fog computing for practical solutions. In this paper, fog assisted the internet of things based quality of service framework is presented to prevent and protect from COVID-19. It provides real-time processing of users' health data to predict the COVID-19 infection by observing their symptoms and immediately generates an emergency alert, medical reports, and significant precautions to the user, their guardian as well as doctors/experts. It collects sensitive information from the hospitals/quarantine shelters through the patient IoT devices for taking necessary actions/decisions. Further, it generates an alert message to the government health agencies for controlling the outbreak of chronic illness and for tanking quick and timely actions.

1. Introduction

The biggest and most important challenge for any government about health care is to protect their citizens from the sudden disease outbreaks in which viruses can spread from one person to another person [5], COVID-19 pandemic is the contemporary element of worriment across the world. It was traced in November 2019, and afterward, it is witnessed that, as like dengue, yellow fever, japanese encephalitis, west nile, and saint-louis encephalitis viruses, COVID- 19 are a large family of viruses that are common in animals [18]. Since then, it has been demonstrated from the lab studies and virus isolations that it has wide geographic dispersion [12,21]. The most common symptoms of the COVID-19 are fever, difficulty in breathing, coughing, tightness of chest, running nose, etc. It is spreading everywhere across the globe. The virus spreads by close contact between the two people. Therefore it is recommended to practice social distancing. Due to coronavirus severity, most of the countries have put a lockdown and travel restrictions for months so that people stay safe at home. If someone develops the symptoms, he/she is advised to remain in isolation for the good of others. This case leads to panic, and people want to be more and more aware of the situation in this crisis [30,31]. COVID-19 has been declared as a public health threat, so the government and various agencies are on their toes to stop the further spread [7,16].

The prominent issue in the area of healthcare is to control this disease effectively [1]. Industry 4.0 can meet personalized facial masking specifications, gloves, and gather health system knowledge for the optimal monitoring and management of COVID-19 patients [13]. Whereas Internet of medical Things cloud and linked network components provide data exchange, report recording, patient recording, knowledge processing and interpretation, hygiene medical treatment, etc. for COVID-19 patients [28].

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Virtual Reality often plays an invaluable role in tackling the pandemic through virtual audiovisual contact [29]. Researchers, technologists, physicians, and other health professionals operate day and night to establish and manage the infection through vaccinations and medical treatment of COVID-19 [9,33]. To stop these outbreaks, the governments are taking the following steps along with isolations and lockdown.

1. Either they hire consultants who can visit manually in every village or town to test their citizens.
2. Or, they need to provide the location of the nearest healthcare agencies to every individual for checkup against the virus infections.

The first step needs a large workforce for successful implementation that can be a costly move. In the second case, each will have to visit the nearest healthcare that may not be feasible regarding conveyance and can be time wasting for some of the people who might not be affected. To control the spread of COVID-19 is still a big issue.

1.1. Objectives

- To develop a framework, which is capable of monitoring the health of citizen concerning COVID-19.
- To provides real-time processing of users' health data with ultra-low latency.
- To predict the COVID-19 infection at a very early stage.
- To generates an emergency alert and medical reports to the user, their guardian as well as doctors/experts.

In this regard, cloud/fog computing integrated with AI can be the best alternative [26]. Various healthcare agencies are adopting cloud/fog computing in the field of healthcare to achieve maximum efficiency to curb various infections, whereas AI is also beneficial to classify the user's health status at a very early stage [6]. Cloud computing is the most effective and suitable method to provide the improved quality of healthcare services, because of ample storage and ease of handling vast amounts of patients' data at a minimal cost [14]. Fog Computing provides a real-time solution with ultra-low delay. Thus, the integration of all these technologies can provide a record-breaking solution to healthcare sector [22].

The proposed framework comprises the design of a healthcare application that can make the initial decision for COVID-19 detection according to symptoms. If the initial test is passed, then this framework provides the nearest location of the Healthcare Center to the affected individual. This furthermore helps in reducing congestions at healthcare centers as only those individuals are visiting the healthcare centers that have passed the initial test of the framework.

2. Literature review

From the last few decades, with the advent of computer technology, many research works had contributed significantly to identify, prevent, and analysis of COVID-19 cases.

Wang et al. [37] developed a weakly-supervised deep learning system for COVID-19 classification and lesion position by 3D CT volumes. The weakly controlled profound research model will reliably estimate the infectious risk of the COVID-19 and discover lesions in the chest CT without warning of training lesions. The simple and high-efficiency algorithm offers a quick way to classify patients with COVID-19, which is useful for managing SARS-CoV-2 outbreaks. Ouyang et al. [20] have developed a dual-sampling network for the automated diagnosis of COVID-19 in chest machine tomography from acquired population pneumonia. A recent online concentration module with a 3D coevolutionary network was suggested to concentrate on the areas of infection in the lungs while making medical decisions. Alsaeedy et al. [2] implemented a modern approach for defining regions with high population density and mobility at risk of spreading COVID-19. A populated environment of moving people involved, especially if they include asymptomatic infectious people along with healthy people, is likely to spread the disease. Hu et al. [11] proposed a weakly controlled profound learning technique to identify and classify CT images for COVID-19 infection. The proposed approach will reduce manual marking criteria for CT images but can also reliably identify infections and discern COVID-19 from non-COVID-19 events. Oh et al. [19] Developed an approach to a patch-based convolutionary neural network with very few trainable COVID-19 diagnostic parameters. They analyzed possible biomarkers in the CXR and noticed that the localized difference in intensity may be biassed towards the globally dispersed COVID-19.

Rajaraman et al. [23] suggested an ensemble techniqueÂ by integrating the most effective machine learning models to enhance classification efficiency. The integrated usage of modality-specific information transfer, iterative process cutting, and ensemble learning have contributed to stronger forecasts. Roy et al. [25] implemented numerous profound models that deal with the related tasks for automated analysis of LUS pictures. A modern, profound network from space transformer networks that simultaneously predicts the severity score for diseases correlated with the input frame and offers a weakly controlled placement of pathological objects. Waheed et al. [36] implemented a system for producing X-ray synthetic chest images by designing the CovidGAN model based on the Auxiliary Classification Generative Adversarial Network. they also suggested that synthetic pictures generated from CovidGAN can be used to boost CNN's efficiency for the detection of COVID-19. Ramchandani et al. [24] proposed a deep learning algorithm to predict the extent of development in contaminated COVID-19 cases in future days. theyÂ propose a new approach for measuring equidimensional images of multivariate time series and multivariate space-time series. The proposed model, by using this new approach, will integrate many heterogeneous features, such as census data, intercountry mobility, intercountry mobility, social distance, past infection development, and learn about complex interactions among these features.

Bahloul et al. [4] have created various mathematical and statistical models for recognizing, monitoring, and predicting the virus spread pattern. One of the most successful epidemiological models to estimate the transmissibility for COVID-19 is the susceptible exposed quarantined recovered death sensitive model. Angurala et al. [3] introduced a drone dependent Covid-19 Medical service for the protection of medical personnel vulnerable to Covid-19 infection. Drones have proved extremely beneficial in all these fields at different stages. Kumar et al. [15] discussed the pandemic COVID-19 structures focused on drones and suggests an interface for the control of pandemic circumstances. Real-time and simulation-based simulations with multiple environments. Tuli et al. [32] uses a better mathematical model to analyze and predict epidemic growth. An ML-based enhanced model has been implemented to assess the future hazard of COVID-19 in countries worldwide.

Based on the literature, it is identified that there is the fog computing integrated with AI can help to diagnose patients at an early stage and process its clinical data with ultra-low delay.

3. Motivation and contributions

The integration of AI and fog computing motivated us to propose smart health framework that can be used to treat massive data and smartly forecast epidemic transmission with ultra-low-delay. It is ideal for applications in which real-time, high reaction times, and low latency are needed. AI models are established in different medical areas, such as cancer, dermatology, brain disorders. Furthermore, a large variety of algorithms for the same form of the domain is implemented for classification. The overall performance of these algorithms is influenced by the repetitive, trivial, and noisy properties in the dataset. Pre-processing approaches such as the collection of features and the reduction of features, remove unnecessary and obsolete attributes, and decreases device noise.

The major contribution of this paper is to propose an integrated fog and AI smart health framework to predict and prevent COVID-19. Finally, we summarise the work and present future directions.

4. Proposed framework

In this section, the proposed quality of service framework using fog computing to predict and prevent of COVID-19 is shown in Fig. 1. It classifies the user's health status of COVID-19 at an early stage and generates alerts to the doctors as well as their guardians according to their health condition. The framework starts with registering citizens through the mobile application or web application along with their static information. The real-time dynamic data is collected through various medical IoT devices. This real-time data is transferred to the fog nodes where AI is applied by using various classification algorithms. Their present health condition is classified as COVID-19 infected or non-infected so that appropriate action can be taken.

The architectural view of the proposed framework is shown in Fig. 1, which contains two subsystems (1) User subsystem and (2) Cloud subsystem. The user subsystem is responsible for collecting the patient's clinical as well as environmental data. It also contains the fog unit where AI is applied, and finally, health data is stored in cloud repositories placed in the cloud subsystem.

4.1. User sub system

The user subsystem is responsible for gathering the real-time information of the Patient where desired information can be uploaded by the patients or through by IoT based medical devices [27]. These medical devices collect the health data in real-time and forward to the fog unit. IoT based medical devices are categorized into two groups:

(1) that are portable attached to the human body directly or indirectly. Body and medical sensors are used to monitor the health condition and keep track of patient health status. These hardware and sensors are used to monitor body temperature, pulse rate, blood pressure, difficulty in

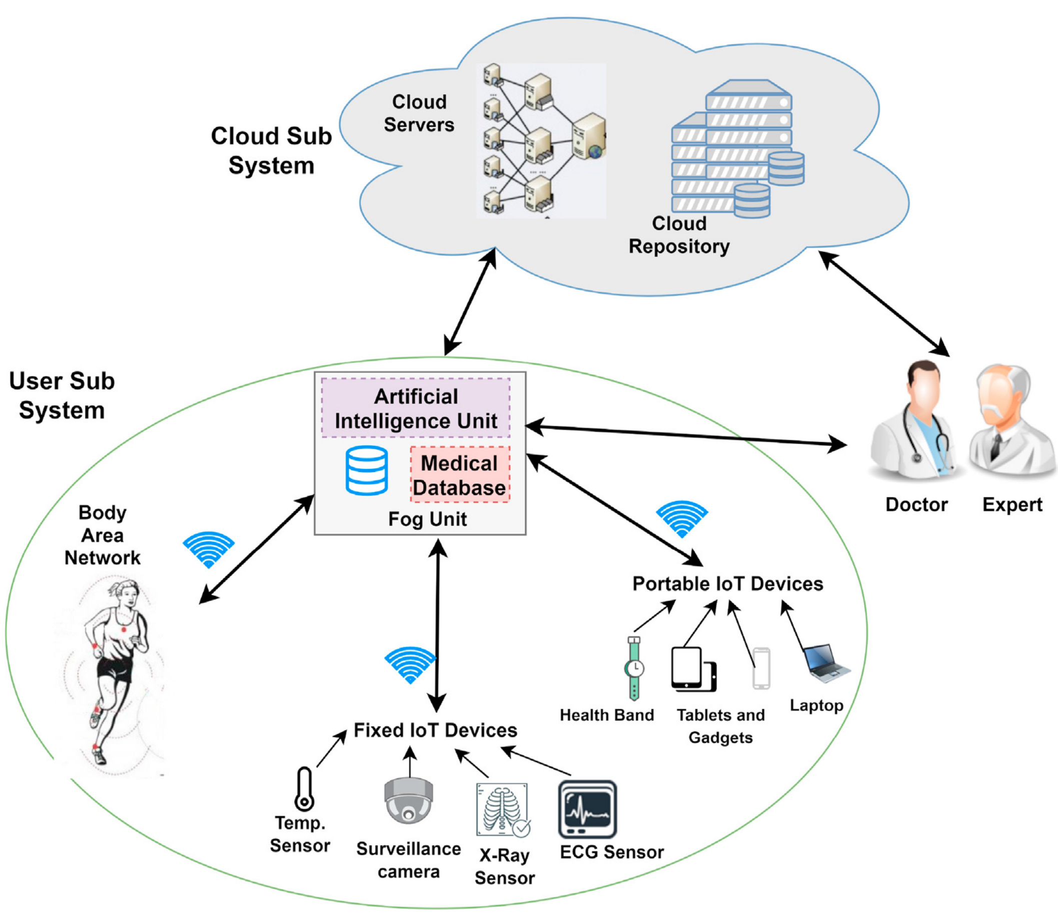

Fig. 1. Proposed framework.

breathing status, coughing, tightness of chest, running nose, etc.;

(2) Fixed devices or smart sensors not attached to the human body. These are used to collect the data from the surrounding of the Patient as room-temperature, humidity, oxygen level, etc.

The critical area of interest of these IoT based medical devices is to provide remote monitoring, consultation, and diagnosis. These devices need a protocol for communication via fog node. Blue tooth, ZigBee, Wifi, WiMAX, etc. provide their best effort for making a connection of short distance. These wireless technologies can establish both short rage communication as well as long-range communication channels for data transmission.

4.1.1. Fog unit

Fog unit contains fog nodes, an AI unit, and a medical database. This fog unit is capable enough to collect data from the IoT based medical devices, process it, store it, and generate alerts accordingly. The fog nodes are very small and smart devices with very limited computing (CPU, memory, storage) capacities. The AI unit decides either the user is COVID-19 infected or not. After that, if the patient is found COVID-19 infected, then his/her information is updated in the medical database. The medical database is placed in the fog unit and sync with the cloud repository. It is used to store the information of the infected patients [22,35]. Also, the information and exact location of the infected person can be shared with the nearest hospital [8].

4.1.1.1. AI unit. The AI unit uses ensemble based techniques to perform clinical diagnoses and suggest treatments [10]. The decision is made based on the risk score estimated using an AI model. Different decisions result in different types of feedback, which are constantly looped for model performance improvement. Different types of feedback have different delay schedules and provide different confidence levels indicating the status of patient health i.e. either COVID-19 Positive or COVID-19 Negative [17,34].

The proposed ensemble based classifier: The COVID-19 detection comes under the classification problem. To enhance the accuracy of COVID-19 prediction three classifiers, Random Forest, Naive Baye's (NB), and Generative adversarial networks, are ensambled and proposed an ensemble based classifier shown in Fig. 2.

The proposed classifier takes the highest performing individual classifiers and weights them to produce a classification in the form of a weighted average. Proposed classifier firstly work on outlier detection and other disciplines have determined genetic algorithms to be a suitable method for finding optimal parameters in high dimensional feature space. The working of proposed ensamble based classifier is shown in Fig. 3.

The algorithm begins with an array of random weights, one for each algorithm. These weights are chosen from the uniform distribution so integer weights are defined by 40 bits or fewer. This allows the genetic algorithm to treat the binary representation of these numbers as "genes" and vary them throughout the evolution process. For each generation, 50 arrays are generated, each with a probability of succession P(s) determined by its fitness. To determine this probability, fitness measurements (fraud costs) are first converted to positive values by the transformation in the equation.

$$f_{pi} = f_i + f_{min} + 1$$

Where f_{pi} the positive fitness of the i^th weight array and is the lowest fitness in the generation. It is important to note that since the cost is used as a fitness metric, low fitness scores are desired. Therefore, f_p values are inverted before probabilities are taken.

$$P(x) = \frac{f_{pmax} + 1 - f_{pi}}{\sum_{i=1}^{n}\left(f_{pmax} + 1 - f_{pi}\right)}$$

Where f_{pmax} is the maximum (worst) fitness score. In turn, all of the weights in the array sum to one. With these probability scores, the following generations are populated by repeatedly choosing two-weight arrays from the existing population and generating a child array with bit-manipulation crossover. Bit flipping is also used to randomly mutate arrays in a population, though this is set to occur rarely. To prevent the ensemble from over-weighting an individual model, a ceiling weight is set at 0.49. Each ensemble optimization via genetic algorithm is given a specific runtime of 1 min.

Random forest: Randomized feature selection reduces a possible correlation among features that can improve the performance. These features give Random Forest(RF) a predictive power that is comparable to the best state-of-the-art algorithms in classification and regression problems.The Algorithm 1 is used to develop a RF. RF possess several properties such as a natural design that allows them to work in a distributed framework, naturally multi-classes, and robust to the noisy system. As a result, RF have become an attractive method for a variety of applications in computer vision such as image classification, pedestrian detection, and facial key point tracking. Many variants of RF have been successfully tailored to specific data mining needs. For a large dataset, RF emerge as a prominent candidate of choice. However, most RF

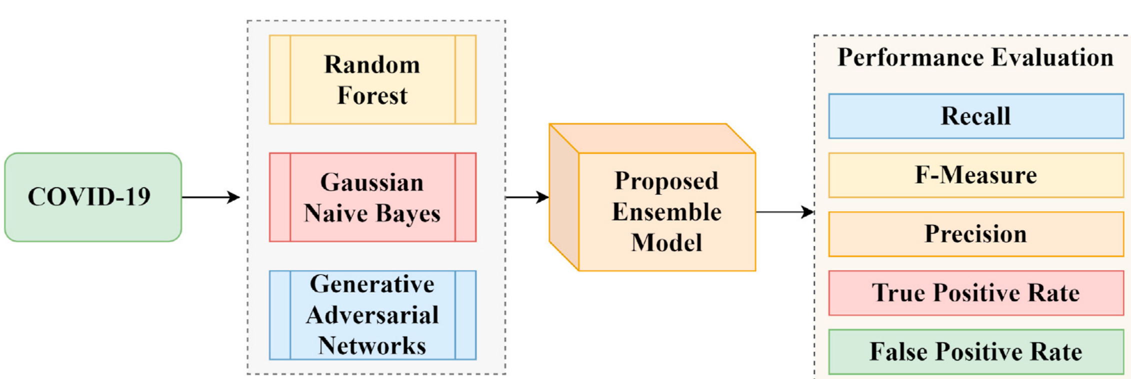

Fig. 2. The proposed ensemble based classifier.

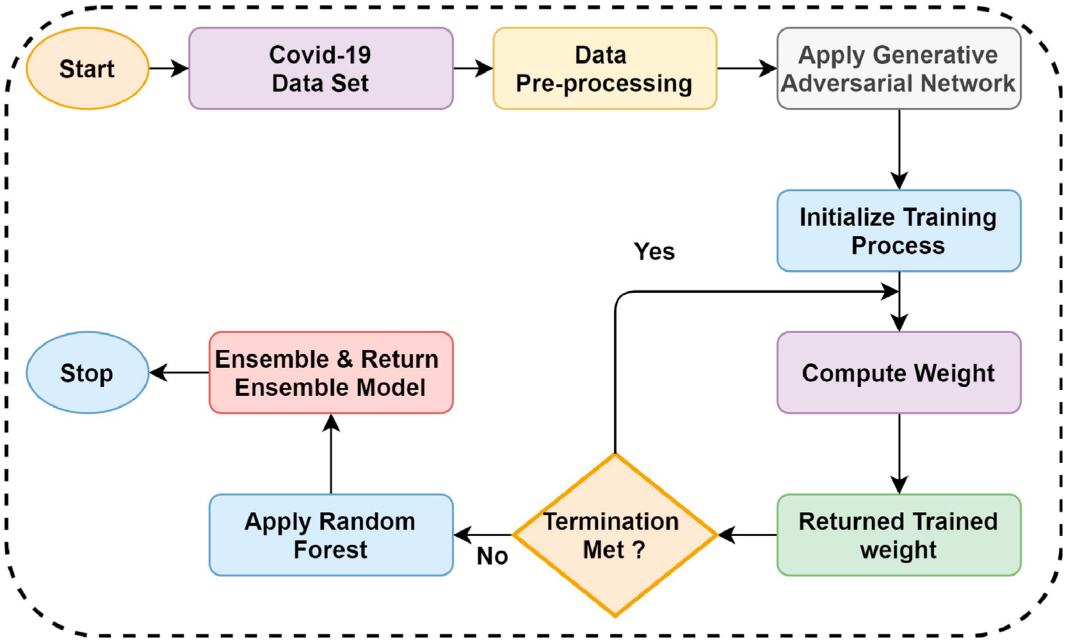

Fig. 3. Working of ensemble framework.

models have been designed and implemented for batch learning where all training data is available at the training time.

Gaussian Naive Bayes The Gaussian Naive Bayes (GNB) classification generates the joint probability distribution as $P(x; y)$ through learning and then uses Bayes theorem to calculate $P(y|x)$. COVID-19 is used bayesian models for their fast prediction generation, and many variant techniques like Bayes minimum risk and Bayesian neural networks have found success in other medical sectors. GNB designs are the third party in addition to type a standard distribution.

$$f(x|\mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma}} e - \frac{(x_\mu^2)}{2\sigma^2}$$

By using an empirically discovered and for each feature, a Gaussian probability distribution can be derived. This information is then be fed into record classification, where is $P(A|B)$ equal to the product of the probabilities of each feature belonging to the normal distribution of that feature $N(\mu B_i, \sigma.B_i)$ derived from training data.

$$P(A_j, B) = P(A)\Pi_{i=1}^{n} P(B_i|A)$$

Generative Adversarial Networks GAN can be a generative model designed by Good fellow. In a GAN startup, two differentiable features (generator G as well as discriminator D), displayed by way of nerve organs CPA affiliate networks, tend to be competitive as well as experienced together, which in turn at some point travel the produced samples to be indistinguishable out of real data [36].

This GAN design throughout this study is dependent on A no GAN lately produced for anomaly diagnosis etc. Most of us customized the main A no GAN by way of together master the encoder E this maps suggestions samples back button to some hidden reflection ounces, and also a generator G as well as discriminator Deborah in the course of training. This lets you help avoid the computationally pricey SGD step intended for recuperating a new hidden reflection in check time. Even as teach the design around the normal facts to help deliver G, Deborah as well as intended for inference, we also outline a new report perform A(x) this steps exactly how anomalous a case in point back button is usually, based on a convex collaboration of a renovation damage LG along with a discriminator-based damage LD.

$$A(x) = \alpha{*}L_G(x) + 1 - \alpha L_D(x)$$

where

$$L_G(x) = ||x - G(E(x))||1$$

$$L_D(x) = \sigma(D(x; E(x)); 1)$$

Where α is often a weighting parameter ranged around (0; 1), (0; 1), σ would be the cross-entropy decline on the discriminator of a being a proper case (class 1). The definition $L_G(x)$ implies how well the actually educated encoder, as well as the electrical generator, could reconstruct a knowledge example. The definition of $L_G(x)$ catches the actual discriminator self-esteem of which a sample hails from the real data distribution. GANs are generative models that are trained to directly estimate data distributions using two functions, a data generating function and an adversarial function called the generator and the discriminator. In other unsupervised development models, GAN is chosen because it does not need to repeatedly sample the input dataset with the Markov chain. The model is straightforward over other unsupervised network models. However, lengthy training challenges and the freedom of model have not been changed.

Algorithm 1. Random Forest

Input : A new incoming data instance d,a Decision tree
Output: An updated Decision tree including d_i

Navigate instance d to leaf node starting from the root of the tree;
Update statistics on attribute values at current node including instance d ;
Evaluate gain function $G(A_i, S)$ on current node for all examples seen so far S.;
if *There exists i such that for all j*, $G(Ai, S) > G(Aj, S)$ **then**
    if *(Training size is less than its threshold and tree depth is less than its threshold* **then**
        split the node with attribute A_i ;
        initial statistics for each child node ;
    end
else
    Select feasible candidate;
end

Algorithm 2. Dataset Generation Algorithm

Result: COVID-19 Data Creation
Input : Patient Symptom
Output: Generate COVID-19 datasets

Step I: N initialize to 1
Step II: for N <= number of entries required do
Step III: allocate values to significant symptoms of COVID-19 based on their probabilities.
Step IV: allocate values to the minor symptom of COVID-19 based on their probabilities.
Step V: create new user data by combining Step III and step IV values generated.
if $PatientID_{Result}$ == *COVID-19 Positive* **then**
    The same user data is already present then
    Discard this data
else
    Add new user data
end
increment N

Algorithm 3. Alert Generation Algorithm

Result: Alert Generated for COVID-19 patıent
Input : Patient COVID-19 report
Output: Alert Generated to guardian,doctors/experts, medical agencies

alert[guardian,doctors/experts, medical agencies]
if $PatientID_{Result}$ == *COVID-19 Positive* **then**
    PatientData ← PatientID , $PatientID_{Result}$
    Send Alert to Guardian, Doctors, Experts, Medical Agencies
else
    send precautions to PatientID
end

4.2. Cloud sub system

In this subsystem, patient data is stored in the cloud repository effectively. The patient needs to provide a username and password to access their data. The critical aspect of cloud storage is the ability for patients to synchronize their data to the medical database located in a fog unit, which can hold a full copy of the data from the remote server. Any changes to patient health conditions are automatically synchronized between the fog medical database and the cloud repositories. The Cloud repository is capable enough to store both static and dynamic data of the patient. The cloud repository is designed with proper authentication and authorization such that no one can access the patients' personal information except the patient himself/herself. The encryption is applied when data is stored in a cloud repository, whereas decryption is applied at the time of accessing data. All the information related to the infected patient is provided to the Government, healthcare agencies, and doctors so that this information could be helpful to the government to control the COVID-19 outbreak. Further, doctors and researchers can utilize this data to analyze the patient's activity for research purpose and their treatment.

5. Experiment setup

The experiment is divided into the following segments:

- Synthetic data generation.
- Training and testing of proposed ensemble based classifier.
- Testing the proposed framework on iFogSim.
- Performance of alert generation.

5.1. Synthetic data generation

To the best of my knowledge, the symptom based data set of COVID-19 is not available in any government repository as UCI, CDC,

Table 1
Symptoms and Status of COVID-19 patients.

S.No.	Symptom	Status
1	Body Temperature	Standard, High, Very High
2	Difficulty in Breathing	No, Very Less, Less, Moderate, High, Very High
3	Room Temporature	< 19,'20–21,22-23,24–25,26-27,28–29,30-31,32 –33,34-35,36–37,38-39,40–41, > 42
4	Tightness of Chest	No, Very Less, Less, Moderate, High, Very High
5	Body Ache	No, Moderate, High
6	Travel history last14 Days	Yes, No
7	Already suffering from	Diabetes, Blood-Pressure, Heart, Asthma, No
8	Running Nose	Yes, No

NHS, etc. which can be utilized directly for analysis. Even though the internet is not able to find any data set, so all possible cases of COVID-19 infection are mapped and generated Synthetic data set by applying the Algorithm LABEL:Algo:DS_Generation which is used systematically under the extreme guidance of physicians, specialist medical officer and medical institutions.

Table 1 is utilized for while providing the COVID-19 symptoms to the algorithm. No possible cause is left while generating the data set.

5.2. Training and testing of proposed ensamble based classifier

The COVID-19 dataset generated by the algorithm is further divided. The 70% of total data is used to train the ensamble based classifier, and rest data is responsible for testing the classifier with various performance measures. This ensamble based classifier is implemented by an open-source language R. The machine learning packages are installed in R studio. Window 7 is installed on Intel i7 2.50 GHz with an 8 GB RAM machine to taking the results of the ensamble based classifier. Before going into the classification phase, preprocessing is performed which contains data cleaning, data integration, data selection, and data transformation. Initially, fourteen attributes are of each patient are collected. The data selection algorithm selects ten attributes for further analysis. In classification phase 10, rotation estimation is selected with ten mutually executive folds. The performance of the ensamble based classifier is stored in terms of recall, and F-measure.

Recall: The value is calculated as the ratio of 'No. of True Positives' and 'the sum of No. of true positives and No. of false negatives'. High Recall value indicates a more efficient classification technique. In the proposed ensamble based classifier, a recall value of 0.93 is achieved which is higher than other classifiers as shown in Fig. 4.

$$Recall = \frac{TP}{TP + FN}$$

F-measure: F-measure is the weighted average of Precision and Recall. Therefore, this score consider the values of both FP(false positive) and FN(false negative).The high value of F- Measure is required for efficient classification techniques. In the proposed data classification, an F - Measure of 0.871 is attained which is higher than other classification techniques is shown in Fig. 5.

$$F - measure = \frac{2 * \frac{TP}{TP+FN} * \frac{TP}{TP+FP}}{\frac{TP}{TP+FN} + \frac{TP}{TP+FP}}$$

5.3. Testing the proposed framework on iFogSim

iFogSim is chosen as a testbed for performance evaluation of the proposed framework. It uses the libraries of CloudSim to perform the simulation. The response time is calculated when the data is accessed at the patients from the fog, with the response time when the data is accessed at the patients from the cloud. Here response

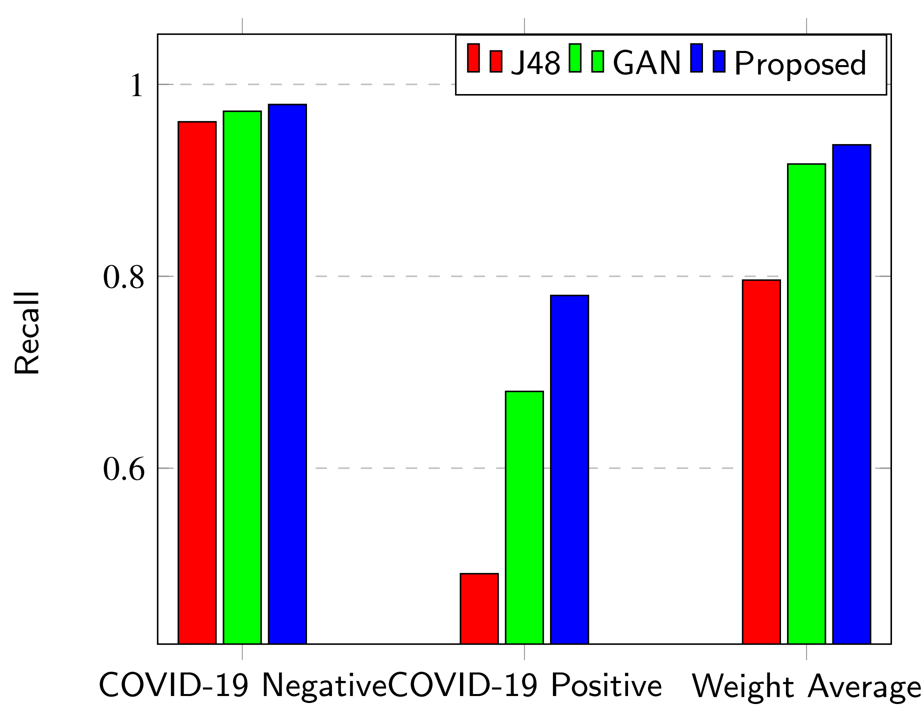

Fig. 4. Recall analysis of classifier.

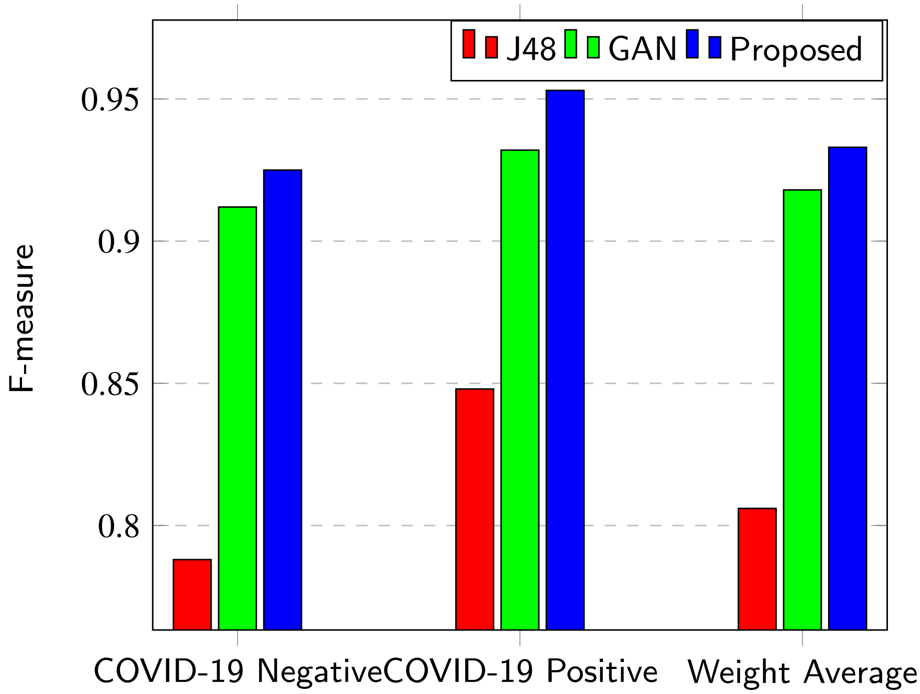

Fig. 5. F-Measure analysis of classifier.

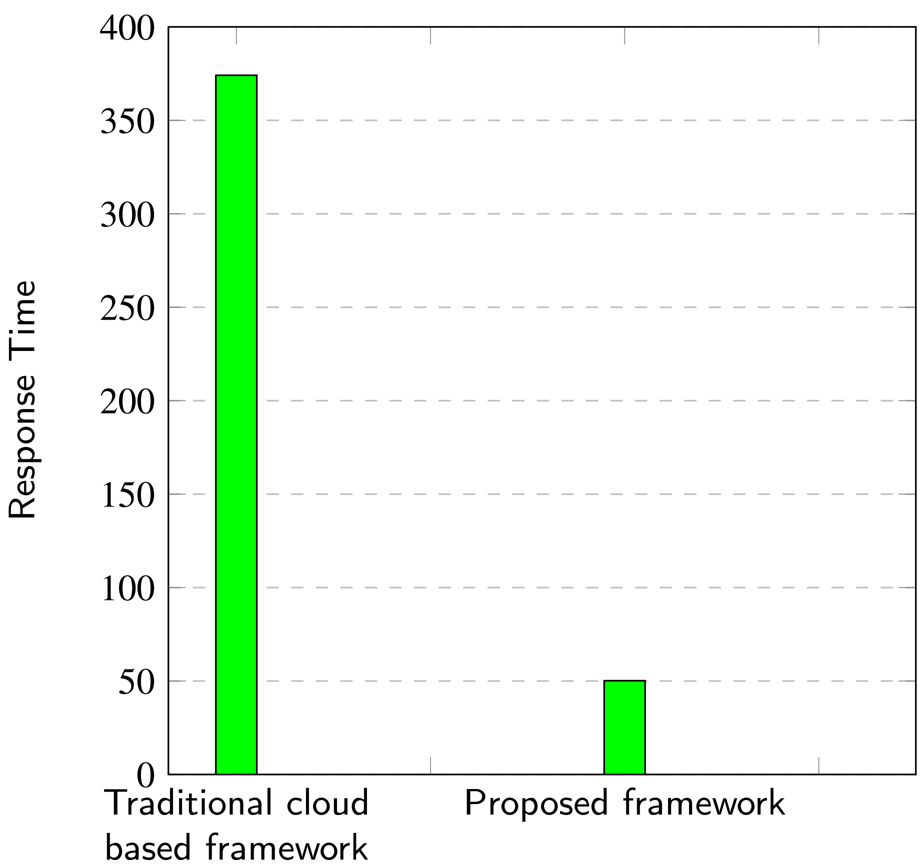

Fig. 6. Overall response time.

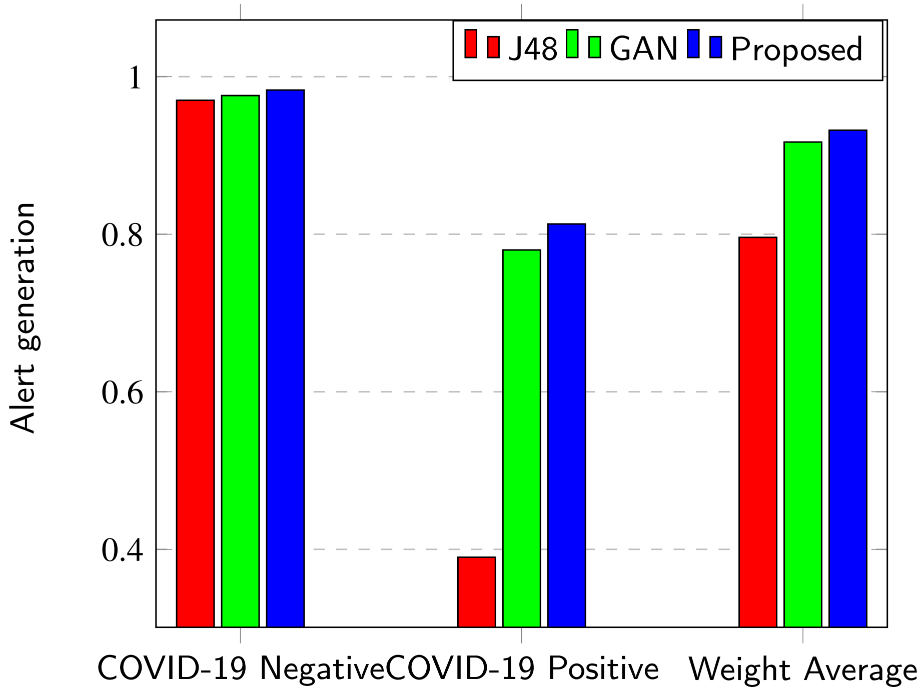

Fig. 7. Alert generation.

time is the time for data transmission from the data generator node to the patient node. When data is accessed from the data center, which is very away from the current location, the response time becomes more as compared to the proposed framework. In the absence of fog nodes, the response time becomes almost 6 times the response time caused by the fog. The comparison of the overall response time is depicted in Fig. 6 which shows that the proposed framework is better than the traditional cloud-based framework.

5.4. Performance of alert generation

Algorithm LABEL:Algo:_alert is presented to process of alert generation. The efficiency of alert generation depends upon the total number of true alerts cases generated by the proposed algorithm. As shown in Fig. 7 the proposed algorithm gives better results compared with other traditional algorithms.

6. Conclusion and future scope

Covid-19 is a communicable disease and therefore it is mandatory to adopt preventive measures. The world is taking a fresh start by leaving behind the tragedy of COVID-19 and moving forward to the era of technology and trade. Cloud/fog computing integrated with AI can help to control this virus outbreak at a little cost. The proposed Quality of Service Framework Using fog Computing to Predict and prevent of COVID-19 is implemented efficiently to control the COVID-19 virus outbreak in various regions of the country. It also updates the location of the affected area on the Google maps and provides the nearest location of the healthcare agency to the user with the help of GPS. The synthetic COVID-19 data of the patients can be used to detect patterns and connections between the attributes that are typical COVID-19 patients. These features can be determined using attribute selection algorithms and classification techniques and used for developing a model which may help in reducing costs and distinctively improve the quality of care.

The limitation of proposed framework is due to the chaotic nature of emergencies, the proposed framework is confronted with the difficulty of working in circumstances that raise difficulties for the usage of devices configured for the regulated atmosphere of a clinical scenario. In a mass casualty emergency, where the doctors have to cope with multiple injuries immediately, they would not be able to respond to warnings until all patients are checked. Medics expect the surveillance device to be most effective for triangulated patients waiting for ambulances. The proposed framework can be used to prioritize patients who require an ambulance.

The future challenges for this research considers the different Quality of Services parameters scalability, security, and fog/cloud-related network traffic details. This research can also be improved in the future with the emerging paradigms of Blockchain, Software-defined Networking, 5G, containers, and Artificial Intelligence. Moreover, the energy-efficient VM system can be used to maximize the energy performance of the overall framework. Also, security aspects can also be improved by examining insider threats and suggesting strategies of deterrence. Introducing a blockchain-based access management framework as a cloud and fog utility may also be evaluated and assessed against different security threats.

CRediT authorship contribution statement

Prabhdeep Singh: Conceptualization, Methodology, Software, Data curation, Visualization, Investigation, Software, Writing - original draft, preparation. **Rajbir Kaur:** Supervision, Writing - original draft, preparation, Validation, Writing - review & editing.

References

[1] J. Alexandre, J.L. Cracowski, V. Richard, B. Bouhanick, et al., Renin-angiotensin-aldosterone system and covid-19 infection, in: Annales d'Endocrinologie, Elsevier, 2020.
[2] A.A. Alsaeedy, E.K. Chong, Detecting regions at risk for spreading covid-19 using existing cellular wireless network functionalities, IEEE Open Journal of Engineering in Medicine and Biology 1 (2020) 187–189.
[3] M. Angurala, M. Bala, S.S. Bamber, R. Kaur, P. Singh, An internet of things

assisted drone based approach to reduce rapid spread of covid-19, Journal of Safety Science and Resilience 1 (2020) 31–35.
[4] M. Bahloul, A. Chahid, T.M. Laleg-Kirati, Fractional-order Seiqrdp Model for Simulating the Dynamics of Covid-19 Epidemic, 2020, 01820 arXiv preprint arXiv:2005.
[5] R. Chen, L. Sang, M. Jiang, Z. Yang, N. Jia, W. Fu, J. Xie, W. Guan, W. Liang, Z. Ni, et al., Longitudinal hematologic and immunologic variations associated with the progression of covid-19 patients in China, J. Allergy Clin. Immunol. 146 (1) (2020) 89–100. https://doi.org/10.1016/j.jaci.2020.05.003.
[6] V.K.R. Chimmula, L. Zhang, Time Series Forecasting of Covid-19 Transmission in canada Using Lstm Networks. Chaos, Solitons & Fractals, 2020, p. 109864.
[7] G.A. Covid, G. Team, F. Landi, C. Barillaro, A. Bellieni, V. Brandi, A. Carfì, C. Cipriani, E. D'Angelo, C. Falsiroli, et al., The geriatrician: the frontline specialist in the treatment of covid-19 patients, J. Am. Med. Dir. Assoc. 21 (7) (2020) 937–938. https://doi.org/10.1016/j.jamda.2020.04.017.
[8] N.Z. Fang, P.M. Castaño, A. Davis, A hospital-based covid-19 abortion case in the early phase of the pandemic, 2020. Contraception.
[9] A. Haleem, M. Javaid, R. Vaishya, S. Deshmukh, Areas of academic research with the impact of covid-19, Am. J. Emerg. Med. 38 (2020) 1524–1526.
[10] C.E. Hastie, D.F. Mackay, F. Ho, C.A. Celis-Morales, S.V. Katikireddi, C.L. Niedzwiedz, B.D. Jani, P. Welsh, F.S. Mair, S.R. Gray, et al., Vitamin d concentrations and covid-19 infection in UK biobank, in: Diabetes & Metabolic Syndrome, Clinical Research & Reviews, 2020.
[11] S. Hu, Y. Gao, Z. Niu, Y. Jiang, L. Li, X. Xiao, M. Wang, E.F. Fang, W. Menpes-Smith, J. Xia, et al., Weakly supervised deep learning for covid-19 infection detection and classification from ct images, IEEE Access 8 (2020) 118869–118883.
[12] R. Jain, M. Young, S. Dogra, H. Kennedy, V. Nguyen, S. Jones, S. Bilaloglu, K. Hochman, E. Raz, S. Galetta, et al., Covid-19 related neuroimaging findings: a signal of thromboembolic complications and a strong prognostic marker of poor patient outcome, J. Neurol. Sci. (2020) 116923.
[13] M. Javaid, A. Haleem, R. Vaishya, S. Bahl, R. Suman, A. Vaish, Industry 4.0 technologies and their applications in fighting covid-19 pandemic, Diabetes & Metabolic Syndrome: Clin. Res. Rev. 14 (4) (2020) 419–422. https://doi.org/10.1016/j.dsx.2020.04.032.
[14] R. Kabarriti, N.P. Brodin, M.I. Maron, W.A. Tomé, B. Halmos, C. Guha, S. Kalnicki, M.K. Garg, N. Ohri, Extent of prior lung irradiation and mortality in covid-19 patients with a cancer history, Advances in Radiation Oncology 5 (4) (2020) 707–710. https://doi.org/10.1016/j.adro.2020.04.028.
[15] A. Kumar, K. Sharma, H. Singh, S.G. Naugriya, S.S. Gill, R. Buyya, A drone-based networked system and methods for combating coronavirus disease (covid-19) pandemic, Future Generat. Comput. Syst. 115 (2020) 1–19. https://doi.org/10.1016/j.future.2020.08.046.
[16] V.M. Kushnir, T.M. Berzin, B.J. Elmunzer, R.B. Mendelsohn, V. Patel, S. Pawa, Z.L. Smith, R.N. Keswani, N.A.A. for the Study, et al., Plans to reactivate gastroenterology practices following the covid-19 pandemic: a survey of north american centers, Clin. Gastroenterol. Hepatol. 18 (10) (2020) 2287–2294.
[17] K.C.N.K. Kwong, P.R. Mehta, G. Shukla, A.R. Mehta, Covid-19, sars and mers: a neurological perspective, J. Clin. Neurosci. 17 (2020) 13–16. https://doi.org/10.1016/j.jocn.2020.04.124.
[18] L. Li, Q. Zhang, X. Wang, J. Zhang, T. Wang, T.L. Gao, W. Duan, K.K.f. Tsoi, F.Y. Wang, Characterizing the propagation of situational information in social media during covid-19 epidemic: a case study on weibo, IEEE Transactions on Computational Social Systems 7 (2020) 556–562.
[19] Y. Oh, S. Park, J.C. Ye, Deep learning covid-19 features on cxr using limited training data sets, IEEE Trans. Med. Imag. 39 (8) (2020) 2688–2700, https://doi.org/10.1109/TMI.2020.2993291.
[20] X. Ouyang, J. Huo, L. Xia, F. Shan, J. Liu, Z. Mo, F. Yan, Z. Ding, Q. Yang, B. Song, et al., Dual-sampling attention network for diagnosis of covid-19 from community acquired pneumonia, IEEE Trans. Med. Imag. 39 (8) (2020) 2595–2605, https://doi.org/10.1109/TMI.2020.2995508.
[21] Y. Pathak, P.K. Shukla, A. Tiwari, S. Stalin, S. Singh, P.K. Shukla, Deep transfer learning based classification model for covid-19 disease, 2020. IRBM.
[22] F. Pietrantonio, M.C. Garassino, Caring for patients with cancer during the covid-19 outbreak in Italy, JAMA oncology 6 (6) (2020) 821–822, https://doi.org/10.1001/jamaoncol.2020.1426.
[23] S. Rajaraman, J. Siegelman, P.O. Alderson, L.S. Folio, L.R. Folio, S.K. Antani, Iteratively Pruned Deep Learning Ensembles for Covid-19 Detection in Chest X-Rays, 2020 arXiv preprint arXiv:2004.08379.
[24] A. Ramchandani, C. Fan, A. Mostafavi, Deepcovidnet: an Interpretable Deep Learning Model for Predictive Surveillance of Covid-19 Using Heterogeneous Features and Their Interactions, IEEE Access, 2020.
[25] S. Roy, W. Menapace, S. Oei, B. Luijten, E. Fini, C. Saltori, I. Huijben, N. Chennakeshava, F. Mento, A. Sentelli, et al., Deep learning for classification and localization of covid-19 markers in point-of-care lung ultrasound, IEEE Trans. Med. Imag. 39 (8) (2020) 2676–2687, https://doi.org/10.1109/TMI.2020.2994459.
[26] R.F. Sear, N. Velásquez, R. Leahy, N.J. Restrepo, S. El Oud, N. Gabriel, Y. Lupu, N.F. Johnson, Quantifying Covid-19 Content in the Online Health Opinion War Using Machine Learning, IEEE Access, 2020.
[27] R.P. Singh, M. Javaid, A. Haleem, R. Suman, Internet of things (iot) applications to fight against covid-19 pandemic, in: Diabetes & Metabolic Syndrome, Clinical Research & Reviews, 2020a.
[28] R.P. Singh, M. Javaid, A. Haleem, R. Vaishya, S. Al, Internet of medical things (iomt) for orthopaedic in covid-19 pandemic: roles, challenges, and applications, Journal of Clinical Orthopaedics and Trauma 11 (4) (2020b) 713–717. https://doi.org/10.1016/j.jcot.2020.05.011.
[29] R.P. Singh, M. Javaid, R. Kataria, M. Tyagi, A. Haleem, R. Suman, Significant applications of virtual reality for covid-19 pandemic, in: Diabetes & Metabolic Syndrome, Clinical Research & Reviews, 2020c.
[30] J.H.C. de Souza, J.L. Ferreira, Development of a corona discharge plasma source for sterilization procedures at atmospheric pressure, in: 2009 IEEE International Conference on Plasma Science-Abstracts, IEEE, 2009, 1–1.
[31] F. Thamburaj, G. Ganapathy, Analysis of genome signature strength of sars coronavirus using self-organizing map neural network, in: 2010 International Conference on Communication and Computational Intelligence (INCOCCI), IEEE, 2010, pp. 28–34.
[32] S. Tuli, S. Tuli, R. Tuli, S.S. Gill, Predicting the Growth and Trend of Covid-19 Pandemic Using Machine Learning and Cloud Computing, Internet of Things, 2020, 100222.
[33] R. Vaishya, A. Haleem, A. Vaish, M. Javaid, Emerging technologies to combat the covid-19 pandemic, Journal of Clinical and Experimental Hepatology 10 (4) (2020a) 409–411, https://doi.org/10.1016/j.jceh.2020.04.019.
[34] R. Vaishya, M. Javaid, I.H. Khan, A. Haleem, Artificial intelligence (ai) applications for covid-19 pandemic, in: Diabetes & Metabolic Syndrome, Clinical Research & Reviews, 2020b.
[35] N. Vukkadala, Z.J. Qian, F.C. Holsinger, Z.M. Patel, E. Rosenthal, Covid-19 and the otolaryngologist: preliminary evidence-based review, The Laryngoscope, 2020.
[36] A. Waheed, M. Goyal, D. Gupta, A. Khanna, F. Al-Turjman, P.R. Pinheiro, Covidgan: data augmentation using auxiliary classifier gan for improved covid-19 detection, IEEE Access 8 (2020) 91916–91923.
[37] X. Wang, X. Deng, Q. Fu, Q. Zhou, J. Feng, H. Ma, W. Liu, C. Zheng, A weakly-supervised framework for covid-19 classification and lesion localization from chest ct, IEEE Trans. Med. Imag. 39 (8) (2020) 2615–2625, https://doi.org/10.1109/TMI.2020.2995965.

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