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Research article

FCMCPS-COVID: AI propelled fog–cloud inspired scalable medical cyber-physical system, specific to coronavirus disease

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ABSTRACT

Medical cyber–physical systems (MCPS) firmly integrate a network of medical objects. These systems are highly efficacious and have been progressively used in the Healthcare 4.0 to achieve continuous high-quality services. Healthcare 4.0 encompasses numerous emerging technologies and their applications have been realized in the monitoring of a variety of virus outbreaks. As a growing healthcare trend, coronavirus disease (COVID-19) can be cured and its spread can be prevented using MCPS. This virus spreads from human to human and can have devastating consequences. Moreover, with the alarmingly rising death rate and new cases across the world, there is an urgent need for continuous identification and screening of infected patients to mitigate their spread. Motivated by the facts, we propose a framework for early detection, prevention, and control of the COVID-19 outbreak by using novel Industry 5.0 technologies. The proposed framework uses a dimensionality reduction technique in the fog layer, allowing high-quality data to be used for classification purposes. The fog layer also uses the ensemble learning-based data classification technique for the detection of COVID-19 patients based on the symptomatic dataset. In addition, in the cloud layer, social network analysis (SNA) has been performed to control the spread of COVID-19. The experimental results reveal that compared with state-of-the-art methods, the proposed framework achieves better results in terms of accuracy (82.28 %), specificity (91.42 %), sensitivity (90 %) and stability with effective response time. Furthermore, the utilization of CVI-based alert generation at the fog layer improves the novelty aspects of the proposed system.

1. Introduction

Healthcare is one of the most extensive factors that need to be efficiently managed for the development of any country, as it is a significant determinant of the well-being of its citizens [1]. A country with an inadequate healthcare system can have a profound impact on the health of its people, resulting in a higher mortality rate, particularly during outbreaks. Therefore, it is imperative for governments to take substantial measures to safeguard their citizens from such prevalent epidemics. The recent outbreak that has affected countries worldwide is the novel coronavirus [2,3] (see Table 1).

COVID-19 (short for "Coronavirus Disease 2019") is an infectious respiratory illness caused by the SARS-CoV-2 virus, which affects the respiratory system in humans [4,5]. This type of virus spreads from person to person and continues to spread when a

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Table 1
List of abbreviations.

Acronyms	Description
MCPS	Medical cyber–physical systems
COVID-19	Coronavirus disease
SNA	Social Network Analysis
GDP	Gross Domestic Product
NHI	National Health Index
ICT	Information and Communication Technology
IoT	Internet of Things
CVI	Covid-19 Vulnerability Index
LDA	Latent Dirichlet Allocation
PCA	Principal Component Analysis
WHO	World Health Organization
cANN	Conventional Artificial Neural Network
K-NN	k-Nearest Neighbor
SVM	Support Vector Machine
RF	Random forest (RF)

healthy person comes into contact with Covid-19 infected patient [6]. Covid −19 can also spread by touching a surface or object contaminated with the virus and then touching one's mouth, nose, or eyes. The symptoms of COVID-19 can vary from mild to severe and may resemble those of other illnesses such as flu, pneumonia, and allergies. As a result, healthcare professionals may face difficulties in identifying and providing appropriate treatment to patients without proper testing [7,8]. One potential solution to address the challenges of identifying and treating COVID-19 is to incorporate Medical Cyber-Physical Systems (MCPS) into the healthcare system. MCPS can assist healthcare professionals in accurately diagnosing and providing effective treatment for patients with COVID-19, thereby improving patient outcomes.

The latest development in information and communication technology (ICT), fog computing, and cloud computing technology makes it feasible to design fog–cloud assisted medical cyber–physical systems (MCPS) [9]. In the recent internet technology era, cyber–physical systems can be interpreted as next-generation systems that combine communication and computing capabilities with the capabilities of physical entities. MCPS is capable of collecting user-centric personal and health-related attributes using mobile or web-based applications and processing real-time health-sensitive data in a fog–cloud environment. Medical cyber–physical systems equipped with fog and cloud layers have the potential to process highly sensitive health data and generate real-time alerts in order to treat patients in a timely manner.

In cyberspace, remote cloud data centers are used to perform multiple operations across the internet such as storing and processing large amounts of data. These services of cloud computing can be accessed using the internet and have the potential to offer several benefits such as high-speed processing, high performance, scalability, lower operational cost, and the ability to store huge volumes of data at a lower cost without any need for additional infrastructure [10]. However, there exist various challenges, such as downtime, low security, high latency in the transmission of analysis results, etc., which make cloud services impossible to use with time-critical healthcare applications. Henceforth, a new computing layer, the fog layer has been introduced which works on the complementary side of the cloud layer [11]. The fog layer is composed of a group of fog nodes, located at the edge of the device, and is responsible for processing data coming directly from the physical device [12]. With a reduced latency in the transmission of health-sensitive information to the stakeholders, the fog layer plays a vital role in MCPS [13,14].

A comprehensive review of medical research articles was conducted to identify research gaps, with a focus on the use of Cyber-Physical Systems (CPS) in healthcare. Although several CPS-based articles were found, none specifically addressed COVID-19 in particular, to the best of our knowledge. In this regard comparative analysis of the recent papers, considering several attributes such as Cyber-Physical Systems (CPS), Predictive Analysis (PA), Alert generation (AG), and Internet of Things (IoT) has been shown in Table 2. Moreover, the survey on various classification algorithms used for COVID-19 predictions has also been carried out and presented in Fig. 1. In the current work, a CPS based on fog-cloud computing for early detection, prevention, and control of Covid-19 has been proposed. The proposed framework is responsible for the prediction of possible cases of COVID-19 disease and the alert generation to the multiple stakeholders of the systems, followed by a social network analysis-based prevention methodology.In addition to that, list of abbrevations were also included in Table 1, for easy understanding of terminology used in the proposed system.

1.1. Major contributions

The major contributions of the proposed framework are listed as:

1. To design an automated fog–cloud-centric medical cyber–physical framework for the detection and prevention of COVID-19 impact at the early stages.
2. Principal component analysis with ensemble learning based classification at fog layer.
3. To calculate the COVID-19 vulnerability index (CVI) at cloud layer and generate real-time alert messages to the users, caretakers, and healthcare professionals.

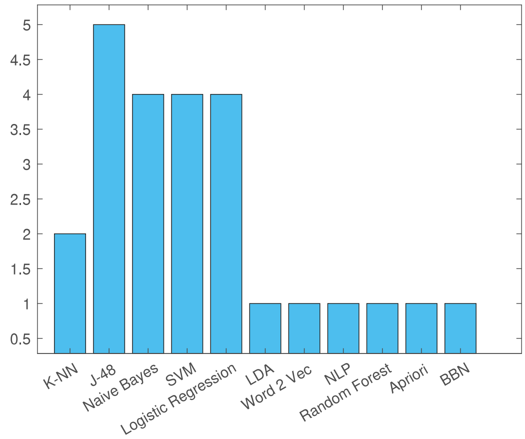

Fig. 1. Algorithms and methods recently used in the literature review to detect MERS-COV disease(2022).

4. To develop a framework for sharing the information of affected patients with government agencies and to take precautionary measures for the control of the COVID-19 outbreak in nearby areas.
5. Finally, Adopting social network analysis-based computational methodology at the cloud layer for preventing the spread of disease with information and suggestions box for infected and uninfected patients.

1.2. Paper organization

The paper is organized into various sections. Section 2 presents the proposed medical cyber–physical based COVID-19 prediction framework. Section 3, comprises of detailed experimental evaluation. In Section 4, a comparative analysis of the proposed framework with previous studies has been carried out. Finally, Section 5 concludes the paper with some recommendations for future work.

2. System model

The proposed framework for early detection, prevention, and control of the COVID-19 outbreak has been presented in Fig. 2. The proposed framework mainly comprises physical space and cyberspace. Physical space is concerned with the task of collecting the user's personal, geographic, and COVID-19-related symptoms specifically either through medical IoT devices or directly from the user's smart devices. In addition, physical space also collects data related to the user's nearby caretakers or healthcare professionals such as name, phone number, and address. Cyberspace utilizes the potential of fog–cloud computing to provide critical healthcare services at a low cost without any delay. The fog layer receives heterogeneous data from the physical space and then performs dimensionality reduction, followed by classification into viable classes: infected or non-infected. The fog layer calculates the Covid-19 vulnerability index (CVI) and correspondingly, warning alerts are sent to stakeholders based on the CVI value. Additionally, the real-time analyzed results and information of a user along with geographic information is also sent to the cloud layer for decision-making and sharing with government agencies for timely arrangement of required resources. Table 3, describes the system workflow of the proposed framework and description of the physical and cyber layers of the proposed framework is explained in the further sub-sections.

2.1. Physical space

Physical space primarily acts as a data collection component of MCPS and is responsible for collecting users' personal, demographic, and COVID-19-sensitive attributes. The information is collected through a mobile application that is connected to the network with the help of cellular technologies. Each user first registers with the system by entering personal details. After successful registration, the system generates a unique tracking number and is assigned to a particular user for future communication. The personal attributes along with their description are given in Table 4. The user is also responsible for entering the symptoms that a particular user is facing in the form of yes or no. Table 5, shows the relevant attributes of COVID-19. These attributes may be further categorized as primary and secondary symptoms. Primary symptoms may be possibly found in almost all old-age users. Instead, secondary symptoms are found in users who may or are suspected of being infected by COVID-19. Physical space primarily deals with different types of participants such as users, caretakers, healthcare professionals, healthcare providers, and other government agencies responsible for providing several medical services to society. The accumulated information is forwarded to cyberspace for further computations.

Table 2
Comparison of the proposed approach with the state-of-the-art approaches.

Reference	Year	Major contributions	CPS	FC	CC	IoT	ML	PA	AG
[15]	2022	Presented a AI-based framework for analyzing Covid-19 trends	✗	✗	✗	✗	✓	✓	✗
[16]	2022	Presented a machine learning based IoT system for COVID-19	✗	✗	✗	✓	✓	✓	✗
[17]	2022	Presented a machine learning approach for autonomous detection and classification of COVID-19 Virus	✗	✗	✗	✗	✓	✓	✗
[18]	2022	Presented a sustainable advanced artificial intelligence-based framework for analysis of COVID-19 spread	✗	✗	✗	✗	✓	✓	✗
[19]	2022	Proposed a framework for determining deterioration rate of infected patients	✗	✗	✗	✗	✓	✓	✗
[20]	2022	Presented an H-CPS COVID-19 framework with a smart X-ray machine interface	✓	✗	✓	✗	✓	✓	✗
[21]	2022	Presented an artificial intelligence-based cyber–physical system for severity classification of chikungunya disease	✓	✗	✗	✗	✓	✓	✗
[22]	2021	Presented an quantum machine learning architecture for COVID-19 classification based on synthetic data generation using Conditional Adversarial Neural Network	✗	✗	✗	✓	✓	✓	✗
[23]	2021	Prediction of COVID-19 risk in public areas using IoT and machine learning	✗	✗	✗	✓	✓	✓	✗
[24]	2021	Cyber-Physical systems and smart cities in India: opportunities, issues, and challenges	✓	✗	✗	✓	✓	✗	✗
[25]	2021	Comparative study of machine learning methods for COVID-19 transmission forecasting	✗	✗	✗	✗	✓	✓	✗
[26]	2020	Presented an IoT-based student healthcare monitoring system	✗	✗	✓	✓	✓	✓	✗
[27]	2020	Presented a healthcare system based on video surveillance	✗	✗	✓	✗	✓	✓	✗
[28]	2020	Presented a smart healthcare system based on Information Fusion and Neural networks	✗	✗	✗	✗	✓	✓	✗
[29]	2020	Presented a model for diabetic chronic disease prediction.	✗	✗	✗	✗	✓	✓	✗
[30]	2020	Presented a smart healthcare and quality of service in IoT using grey filter convolutional based cyber physical system	✓	✗	✗	✓	✓	✓	✗
[31]	2020	Presented a fog-cloud based cyber–physical system for ulcerative colitis diagnosis, stage classification and management	✓	✓	✗	✗	✓	✓	✗
[32]	2018	Presented survey on the use of IoMT in Cyber-Physical Systems.	✓	✗	✓	✓	✗	✗	✗
Proposed	–	An Intelligent Healthcare system for the diagnosis and management of COVID-19	✓	✓	✓	✓	✓	✓	✓

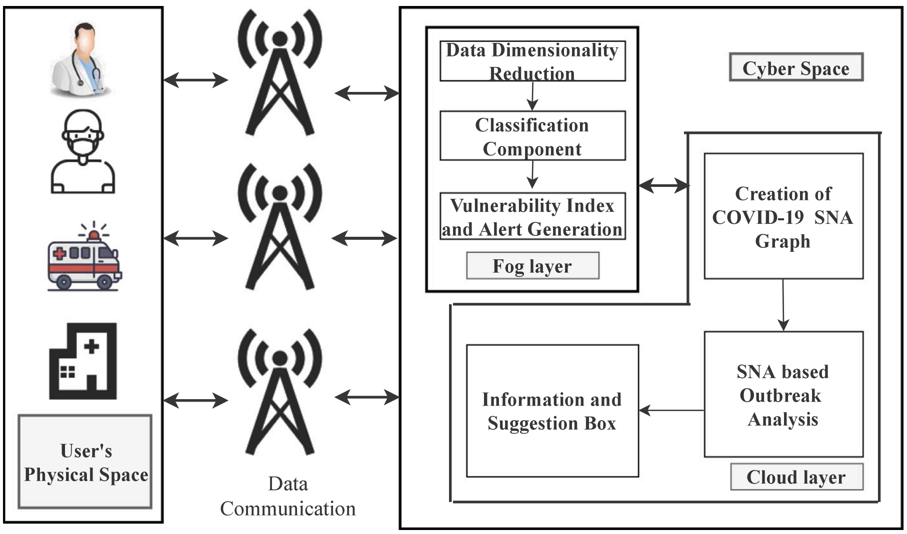

Fig. 2. Proposed medical cyber–physical framework for coronavirus detection and prevention.

Table 3
Work-flow for prediction and prevention of Covid-19 Outbreak.

	Working of the proposed framework
Step 1	Each user is required to register with the MCPS. Upon successful registration, a distinct tracking number is allocated to the user.
Step 2	User input their personal information along with symptoms faced by them through the mobile or web-based application.
Step 3	The inputted information is transferred to cyberspace, which is composed of fog and cloud layers.
Step 4	In the fog layer, the ensemble learning technique-base classifier is employed which classifies the user into different categories such as non-infected or possibly infected, and the user's COVID-19 vulnerability index is computed and alerts are sent to the stakeholders.
Step 5	The information about possibly infected or suspected cases of COVID-19 is transferred to the cloud layer for storage and further computation using SNA metrics.
Step 6	The information in the cloud layer about suspected cases may be used by government agencies to take precautionary measures to prevent the outbreak of COVID-19 in nearby areas.

Table 4
Personal attributes of a patient.

S.No.	Attribute	Description	Datatype
1	Unique ID	Any Identification number assigned by the country for unique identification of a person	Integer
2	Reference no.	A unique number assigned to a patient upon successful registration with the CPS	Integer
3	Name	Name of a patient	String
4	Age	Patient's age in years	Integer
5	Gender	Gender of a patient (Male or Female)	Character
6	Address	Permanent address of user's home and office	String
7	Mob. No.	Mobile No. of a user	Integer
8	Caretaker's contact no.	Mobile No. of a caretaker	Integer
9	Caretaker's Address	Permanent address of caretaker	String

Table 5
COVID-19 related symptoms.

Primary Symptoms	User's Response	Secondary Symptoms	User's Response
Hypertension	High/low	Sudden Fever	Yes/No
Diabetes	Yes/No	Dry cough	Yes/No
Cardiovascular disease	Yes/No	Sore throat	Yes/No
Vomiting	Yes/No	Difficulty in breathing	Yes/No
Lethargy	Yes/No	Chest Pain	Yes/No
Headache	Yes/No	Bluish lips or face	Yes/No
Red Eyes	Yes/No	Travel history to Infected or risk-prone area	Yes/No
Normal cough	Yes/No	Exposure to Infected Human	Yes/No
Lung Disease	Yes/No	Regular Visits to Hospitals	Yes/No
Body Temperature	Yes/No		

2.2. Cyber space

Cyberspace is responsible for performing computation on the data forwarded by distinct entities in the physical space. Cyberspace analyzes the data for possibly infected COVID-19 cases and generates alerts to the caretakers and hospitals for further investigation. Cyberspace is formed by the integration of two layers namely, cloud and fog layer. The fog layer in cyberspace collects the heterogeneous data, performs dimensionality reduction, and the task of classification of users into possibly suspected cases and non-infected case. The fog layer that consists of multiple fog nodes acts as a middleware between physical devices and cloud servers. Fog nodes with limited storage capacity process the health-sensitive data in real time. Due to the limited storage capacity of fog nodes, cloud servers are used to perform storage tasks. The data stored in cloud servers can be used by government agencies to take crucial decisions to avoid the spread of the highly prevailing outbreak. The description of fog and cloud layers in cyberspace is given ahead.

2.2.1. Fog layer

The fog layer in cyberspace includes four components namely, data dimensionality reduction, classification component, vulnerability index calculation, and alert generation component.

(a) Data dimensionality reduction:. The data set used for the prediction and prevention of COVID-19 may contain a wide range of attributes. Many of these attributes are highly correlated, analyzing and processing such a large amount of data is very expensive and time-consuming. Moreover, the storage of such a huge volume of data becomes a tedious task, leading to high storage requirements. In order to eliminate the inconsistency in the system, a dimensionality reduction component, namely Principal Component Analysis (PCA) is used in the fog layer. The data dimensionality reduction component is responsible for reducing the attribute set by considering only a small set of relevant attributes, thereby improving interpretability without losing any prediction accuracy.

The data dimensionality reduction component reduces the data in a higher-dimensional space to a lower-dimensional space with fewer attributes, which are called Principal Components (PCs). Algorithm 1, details the working principle of data dimensionality reduction. Consider a data set DS with m attributes and n instances. Any instance of the data set is defined by a set of attributes given by Eq. (1).

$$\left\{x_1, x_2, x_3, \dots \dots, x_m\right\} \tag{1}$$

This dataset is passed as an input to the principal component analysis. The algorithm generates a new transformed dataset DS_T with the fewer number of attributes defined by $DS_{T_{n*k}}$ where k denotes the number of principal components. Therefore, the converted data set $DS_{T_{n*k}}$ is used for further analysis

Algorithm 1: Working of PCA based data dimensionality reduction

Input:: A dataset DS with m attributes and n instances; where an instance of a dataset is represented by a range of attributes $x_1, x_2, x_3, \dots, x_m$.
Output: A transformed dataset DS_T with reduced feature-set.

1: Calculate the mean for each attribute of DS by using $x_i^- = 1/n \sum_{i=1}^{n} x_i$
2: Compute the deviation from mean corresponding to each data value such that the resultant value is obtained using $\left(x_{ji} - x_i^-\right)$ where $1 < \mathrm{j} < \mathrm{n}$ and $1 < \mathrm{i} < \mathrm{m}$ and is represented by matrix DS_m.
3: Calculate Eigenvalues $(e_1, e_2, e_3 \dots, e_m)$, for m attributes such that $\det(\mathrm{CoV} - \mathrm{eI}) = 0$. Also calculate eigenvectors corresponding to calculated eigenvalues.
4: Sort the eigenvectors in the descending order of their eigenvalues and take first ' k' eigenvectors so that variance is maximized and store in a matrix $M = (m_1, m_2, m_3 \dots, m_m)$, of dimensions $m * k$ where m_i, denotes eigenvector.
5: New Data matrix of dimensions m*k is formed such that $DS_T = (DS) * M$
6: Exit.

(b) Event classification:. The classification component in the fog layer is responsible for classifying users into one of the two categories i.e. possibly infected or uninfected. For efficient prediction and prevention of COVID-19, it is very important to provide accurate classification results to the user or caretakers. To achieve this purpose, an ensemble learning technique has been utilized. The ensemble is a popular learning technique that involves integrating the output of multiple machine learning models to generate a high-level model that makes predictions with higher accuracy [33]. These individual machine-learning models are also called base learners. The proposed ensemble classifier has been designed using three base learners namely, SVM, K-NN and RF. Fig. 3, shows the conceptual framework of the newly formed ensemble classifier.

The proposed ensemble classifier uses a DS_T dataset with n number of instances, and m features respectively. Each instance of the dataset is defined by a set of COVID-19-related features $(x_1, x_2 \dots x_m)$. Moreover, the data set consists of two types of labeling results, namely infected and uninfected. Initially, the reduced data set with the most critical feature set is randomly divided into a training set and a test set. Each base learner uses 80% of the data for training using the 10-fold cross-validation technique, and the remaining 20% of the data is used for testing and validation purposes. Various hyper-parameters for each of the base learners are adjusted using a grid search parameter tuning scheme. Parameter adjustment helps to obtain the best model architecture, thereby reducing training errors. After successful training, the model is tested using a test dataset. For each instance, i present in the dataset, the posterior probability score for each class is computed to determine the outcome of an instance i. The class with the highest value of posterior probability determines the outcomes chosen by each base learner. Various ensemble learning techniques based on voting such as weighted-average voting, average voting, and majority voting are available in the literature. Amongst all, the weighted average voting is superior to other technologies and is used for the proposed work.

In the weighted-average voting-based ensemble learning model, weights are assigned to the base learners $(B_1, B_2 \dots B_m)$ such that $\sum_{i=1}^{m} w_i = 1$. Each base learner is assigned the weight, according to its performance on the test data and the final class is determined using the formula given in Eq. (2) as:

$$\hat{y} = W_1 \times \mathrm{P}\left(B_1(X)\right) + W_2 \times \mathrm{P}\left(B_2(X)\right) + \cdots \quad + W_M \times \mathrm{P}\left(B_M(X)\right) \tag{2}$$

Where, $B_1, B_1, \dots, B_m$, represents the base learners and the value of $\hat{y}$ determines the predicted class.

The user is classified as possibly infected only if the value of $\hat{y}$ evaluates to be more than 0.5. Correspondingly, CVI for the respective user is computed and alerts are generated to the various stakeholders for timely action.

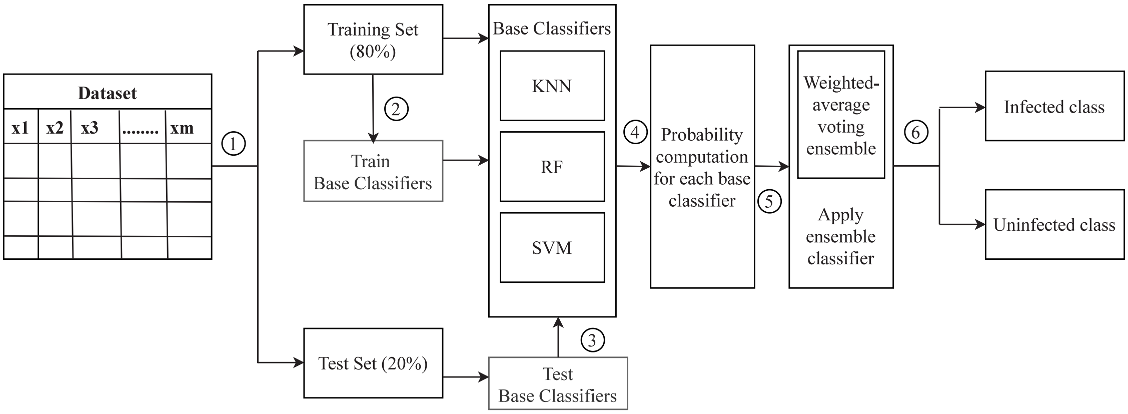

Fig. 3. Ensemble learning based classification.

Algorithm 2: Working of Voting-ensemble classification algorithm

Input: : A dataset DS_T with n number of instances, m features respectively, and a series of m base learners.
Output: A predictive outcome as infected or uninfected.

1: Split the dataset into the training set and test set with 80% of total data in the training set.
2: **for** i = 1 to M **do**
3: Train the base classifiers using a 10-fold cross-validation scheme and tune the hyper-parameter for each base classifier $(B_1, B_1, \dots B_m)$ using grid search parameter tuning scheme.
4: Test and evaluate the performance of each base classifier $(B_1, B_1, \dots B_m)$ using the test dataset.
5: Compute the class probability and predict the result of $(B_1, B_1, \dots B_m)$ for all instances in test dataset.
6: **end for**
7: Apply the weighted-average voting scheme and obtain the classified result of the ensemble classifier.
8: Exit.

(c) Vulnerability index computation and alert generation:. Once the user's current status comes under the infected category, the vulnerability index component sends real-time alerts by computing the CVI of the user. The CVI computation is based on the conditional probability status of the user for various events. Real-time events, such as medical history, COVID-19-specific health attributes along with environmental, and location-specific attributes also play an important role in computing CVI. The formula for computing CVI, concerning the time for various events E_i is

$$CVI = P\left(\frac{VHI}{U_{i=1}^{n} E_i}\right) \tag{3}$$

Where VHI represents the vulnerability category as infected. If the CVI value is higher than the predefined threshold, the user will automatically receive a warning about the required action and go to a nearby hospital for a COVID-19 test. Moreover, after the test, if the user is diagnosed with a positive test, the user will be isolated in the hospital for the next few weeks until recovery. These alerts are also stored in cloud data servers and used to share information with healthcare professionals and government agencies to overcome the spread of coronavirus disease. Therefore, the user's CVI improves the decision-making capabilities of doctors and government agencies by reducing the threat of coronavirus spread. Algorithm 3 demonstrates the detailed working of automatic alert generation in real-time.

2.2.2. Cloud layer

The Cloud layer includes three components, namely cloud storage, SNA-based graph creation and computation, suggestion box, and health communication. A detailed description of each component is given ahead.

(a) Cloud storage. The main goal of the cloud-based storage component is to store information related to infected patients or uninfected patients, and the location of COVID-19-infected areas. This component also includes compiled medical data and a security mechanism to grant privileges to the other entities in physical space for accessing necessary information. In addition, diagnostics and emergency warnings from the fog layer are also stored in the cloud layer for further incident-based actions in the future. Cloud storage stores historical records of infected and uninfected patients to create a dynamic global SNA graph. The detailed process is shown in Algorithm 4. Henceforth, after forming the global instance of a graph, the area is covered based on Fig. 4. Moreover, the final hexagonal structure formation and route prediction is based on SNA outbreak prevention strategy, discussed below.

Algorithm 3: Fog computing based alert generation

Input:: User's classified category, an event happening probability, and predefined Threshold Value (PTH).
Output: Alerts to the users and other stakeholders.

The user classification, key health attributes, and events are categorized.
if user's classified category is infected **then**
    Calculate a future compromised user's coronavirus vulnerability index (CVI) and the probability of multiple time stamp occurrences.
else if CVI exceeds PTH **then**
    The user is in the infected stage and an immediate message is sent to the user and caregiver.
else
    User is in safe stage compute its events probability after Δt time-interval.
end if
Exit.

Algorithm 4: To create a dynamic coronavirus SNA graph

Input:: Infected or Uninfected user, resident address, and traveling history.
Output: Updated Global coronavirus SNA graph.

Get a classified category of user, resident address, and visited locations.
if user classified category is infected after COVID-19 test **then**
    Create two nodes or vertices one for the user and the second for his/her residence with a Red color, connected through the edge.
    Get the visited locations of the user through the mobile app.
else
    Create a new node of the user's residence address with Green color.
    Get traveling locations of the user.
end if
for i = 1 to N **do**
    if visited location [i] is already in the graph **then**
        Create a new edge between the visited location [i] and the user. Change the area color by user category.
    else
        Create a new node with visited location [i].
        Create an edge between the visited location [i] and the user. Change the area color by user category.
    end if
end for
Exit.

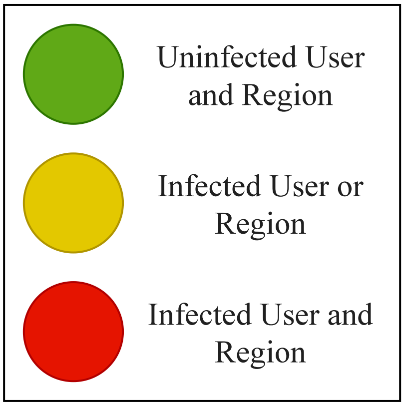

Fig. 4. SNA graph nodes color indications.

(b) SNA metric for prevention of outbreak. SNA graphs play a vital role in mapping important information related to the COVID-19 pandemic and future directions to mitigate its impact on the community.

Definition 1. Degree centrality ∂_p determines the number of direct contacts between users and other people, as an indicator of correlation. In the SNA graph G(V, E) with a set of vertices and edges, the adjacency matrix A = (a_{ij}) can be used to formalize $(\partial_p(x))$ as:

$$\partial_p(x) = \sum_{i=1}^{n} a_i x \tag{4}$$

Therefore, the higher the centrality score, $\partial_p(x)$ of a node x, the more connections there are to node x.

Definition 2. Proximity centrality ∂_c can be defined as users who are close to other nodes can spread the coronavirus very effectively through the network.

$$\partial_c(x) = \frac{1}{\sum_{i=1}^{n} d_G(x,i)} \tag{5}$$

In this equation, by using the reciprocal, we can say that as the distance from another node decreases, the proximity centrality value increases.

Definition 3. If the network members are on the shortest path as much as possible between other pairs of nodes, the network members are considered to be well connected, and hence, In betweenness centrality ∂_b is higher.

$$\partial_b(x) = \sum_{i=1, i\neq x}^{n} \sum_{j=1, j<i, j\neq x}^{n} \frac{g_{ij}(x)}{g_{ij}} \tag{6}$$

Here, $g_{ij}(x)$ represents the number of shortest paths from node i to node j, and gij(x) denotes the number of those paths which pass through the node x.

Definition 4. The eigenvector centrality ∂_E is based on the idea that the relationship with a node with a higher degree of interconnection contributes more to its centrality than a relationship with a node with a lower degree of interconnection. For a user x, the $\partial_E(x)$ can be defined as:

$$\partial_E(x) = v_x = \frac{1}{\lambda_{\max}(A)} \sum_{j=1}^{n} a_{jx} v_j \tag{7}$$

With $\mathrm{v} = (\mathrm{v}_1, \mathrm{v}_2 \dots \dots \dots, \mathrm{v}_n)^T$, refers to an eigenvector for the maximum eigenvalue $\lambda_{\max}(A)$ of the adjacency matrix.

Definition 5. The formation of clusters in any region is very important. It will take strict measures such as blocking the area to help government agencies seize the area or region and restrict people's travel. The global clustering coefficient is based on triplets of nodes. It is defined as:

$$\mathrm{GCC} = \frac{\text{number of closed triplets (or 3*triangles)}}{\text{total number of triplets (both open and closed)}} \tag{8}$$

Local clustering coefficient: The neighborhood N_i of vertex V_i is defined as its directly connected neighbors, as follows:

$$N_i = \{v_j : e_{ij} \in E, e_{ji} \in E\} \tag{9}$$

We define K_i as the number of vertices, $|N_i|$ in the neighborhood, N_i, of a vertex.

The local clustering coefficient $|c_i|$ for a vertex $|v_i|$ is given by the proportion of links between the vertices in its neighborhood divided by the number of links that could possibly exist between them. An undirected graph has the property that e_{ij} and e_{ji} are considered identical. Therefore, if vertex $|v_i|$ has $|k_i|$ neighbors, there may be$|k_i|$ $(|k_i|$ -1)/2 edges between vertices within the neighbors. Thus, the local clustering coefficient for undirected graphs can be defined as:

$$C_i = 2\frac{|\ (e_{jk} : v_j, v_k \in N_i, e_{jk} \in E \ \|}{k_i\,(k_i - 1)} \tag{10}$$

(c) Information and suggestions box. The World Health Organization has been working with governments and experts to provide timely advice and help prevent the spread of the epidemic in affected countries. According to the World Health Organization (WHO), several guidelines have been proposed to reduce the spread of COVID-19. The detailed description of the guidelines for Uninfected and COVID-19 infected patients is given in Table 6.

According to the results of the SNA graph, users can be divided into two categories. The users who fall under the red zone are considered as severely infected and the others who fall under the orange zone are the users with a higher chance of being infected. The users who fall under the orange zone are those who have a travel history of COVID-19-infected countries or the persons who have been in contact with the infected users. The detailed guidelines for both the category of users are depicted in Tables 7 and 8.

Table 6
Guidelines for uninfected users.

S.No	Guidelines
1	All users under the age of 12 and over 60 years of age are advised to stay at home as they are more prone to COVID-19 due to their lower immunity level.
2	Users are suggested to wash hands thoroughly at regular intervals by using alcohol-based hand sanitizer and prevent touching of eyes, nose, and lips.
3	Maintain social distancing and avoid unnecessary travel.
4	Healthcare professionals must maintain proper hygiene, wear masks, gown, and gloves, and avoid direct contact with family members.
5	Do not share wearings, eating utensils, and food or drinks with others.

Table 7
Guidelines for infected red zone users based on SNA graph.

S.No	Guidelines
1	All the COVID-19 infected users are advised to take regular COVID-19 tests at hospitals and stay in isolation wards set up in nearby government hospitals until they found COVID-19 negative for the two consecutive times.
2	All the family members of an uninfected user are advised to visit the hospital for the COVID-19 test.

Table 8
Guidelines for infected orange zone users based on SNA graph.

S.No	Guidelines
1	Users are advised to stay in isolation for at least 14 days.
2	Share information regarding any recent travel immediately with the healthcare provider after arriving from an infected area.
3.	Users with flu or any symptoms must inform the nearby healthcare agencies and test themselves for possible COVID-19 infection.
4.	While Coughing or sneezing, cover nose and mouth with a flexed elbow.

3. Experimental setup and performance analysis

In this section, various experiments have been carried out to evaluate the performance of the proposed framework. The experimentation has been conducted on a system with the following specifications: Intel(R) Core(TM) i7-11700 processor, memory capacity 16 GB, clock frequency 2.50 GHz, and 64-bit Windows-11 pro operating system. This section is composed of multiple sub-sections and a description of each sub-section is given ahead.

3.1. Dataset description

To evaluate the performance of the proposed framework, a dataset with a large number of instances is required. After a rigorous search of COVID-19 symptoms on the internet, few symptoms-based datasets are found. The description of COVID-19 and its related datasets have been presented in Table 9. Based on the consultation with medical experts, the probabilistic value for the presence of each attribute is obtained and presented in Table 10. Based on the probabilistic values, numerous COVID-19 cases are created for getting effective results. Algorithm 5, describes the working of COVID-19 dataset generation.

3.2. Data dimensionality reduction analysis

The best-case data sets generated using Algorithm 5, are further reduced using PCA for efficient and more rigorous results, using the R Studio tool. Multiple principal components with eigenvalues and cumulative variance for system stability are shown in Fig. 5.

Algorithm 5: Dataset generation for COVID-19

```
Input: : Data containing COVID-19 symptoms and number of distinct cases required.
Output: A dataset with the distinct COVID-19 symptoms.
Initialize i = 1.
for i = 1 to N do
  Assign values to attributes as primary symptoms based on probabilities set in Table 10.
  Assign values to attributes as secondary symptoms based on probabilities set in Table 10.
  Bootstrap datasets by adding new cases, combining all COVID-19 symptom values based on the probability distribution set.
  if new case with same data values for attribute-set is already present then
    Discard entry of new record.
  else
    Add the new record to the database.
  end if
  increment i by 1.
end for
Exit.
```

Table 9
Coronavirus datasets description and its available sources.

1.	Dataset of patients affected by MERS-CoV in Saudi Arabia consisted of all cases in the second half of 2016. Available on the Ministry of Health Control and Command Centre website.	[https://www.moh.gov.sa/Ministry/Open-Data/Pages/default.aspx].
2.	Articles collected from the Internet reported by 153 news media outlets in Korea and comments associated with these articles from day 1 (the first confirmed case on May 20, 2015) to day 70 (the de facto end declared by the government on July 28, 2015), in addition to short-text comments on news articles in Twitter and Facebook.	[http://www.naver.com]
3.	A dataset was collected from UCI. -A dataset containing 322 records, 92 infected cases, and 230 uninfected cases was obtained. Each record contained 24 attributes.	[https://www.nejm.org/doi/full/10.1056/nejmoa1306742]
4.	ARS and MERS Spike glycol protein data from National Center for Biotechnology Information database.	[www.ncbi.nlm.nih.gov]
5.	COVID-19 dataset on Kaggle	[http://www.kaggle.com/imdevskp/corona-virus-report/version/98/kernels]

Table 10
Probability for COVID-19 symptoms.

Primary Symptoms	User's Response	Secondary Symptoms	User's Response
Hypertension	0.08	Sudden Fever	0.17
Diabetes	0.12	Dry cough	0.16
Cardiovascular disease	0.07	Sore throat	0.08
Vomiting	0.15	Difficulty in breathing	0.15
Lethargy	0.13	Chest Pain	0.05
Headache	0.06	Bluish lips or face	0.03
Red Eyes	0.09	Travel history to Infected or risk-prone area	0.30
Normal cough	0.12		
Lung Disease	0.10		
Body Temperature	0.08		

The figure depicts the first five PCs have eigenvalues greater than 1 and cumulative variance near 90% for different PCs. Therefore, the first five PCs are considered for accumulating most of the information and are further forwarded to the ensemble learning classifier for initial analysis.

3.3. Performance analysis of classification model at fog layer

In the fog layer, the proposed framework uses an ensemble learning technique for the classification of patients based on their symptoms. Determining the performance is one of the major aspects to judge the quality of the framework. Therefore, the performance of the proposed framework has been evaluated using various metrics as follows:

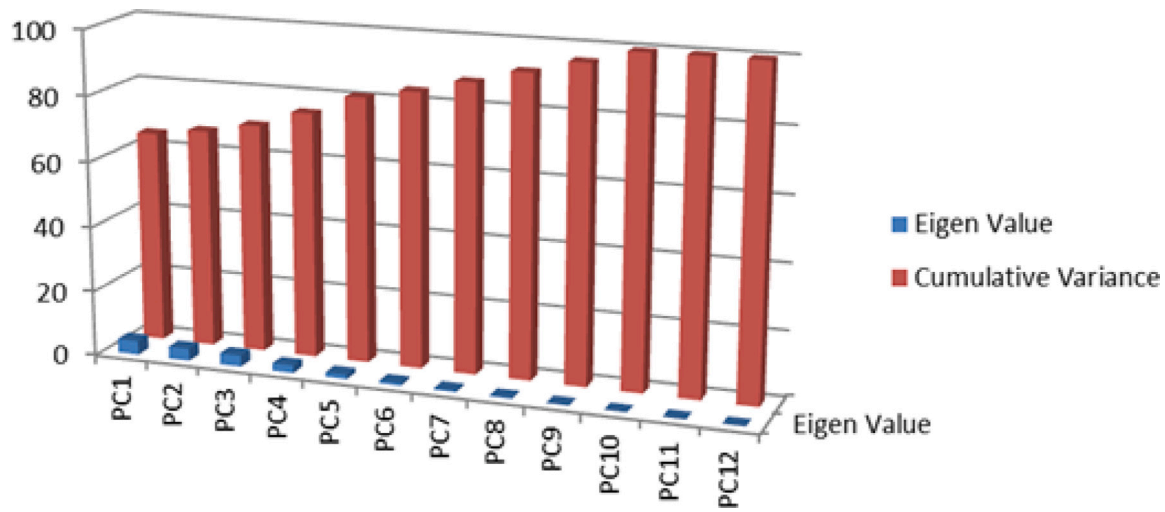

Fig. 5. Scree Plot PCA.

Table 11
Correlation analysis with 95% confidence interval.

Measure	cANN	SVM	k-NN	RF	Proposed
Pearson's Correlation coefficient (τ)	τ= 0.53 ± 0.09	τ= 0.51 ± 0.06	τ =0.45 ± 0.07	τ= 0.48 ± 0.08	τ= 0.64 ± 0.08
Kendell rank coefficient (κ).	κ =0.38 ± 0.021	κ =0.29 ± 0.015	κ =0.14 ± 0.070	τ= 0.40 ± 0.024	κ = 0.48 ± 0.034

1. Accuracy: Accuracy represents the fraction of the number of correct predictions to the total number of predictions made.
   $\text{Accuracy} = \frac{T_P + T_N}{T_P + T_N + F_P + F_N}$
2. Specificity: Specificity measures the number of predictions correctly identified as negative out of the total actual negatives.
   $\text{Specificity} = \frac{T_N}{T_N + F_P}$
3. Sensitivity: Measures the number of predictions correctly identified as positive out of the total actual positive predictions.
   $\text{Sensitivity} = \frac{T_P}{T_P + F_N}$
4. F-score: F-score measures the effectiveness of predictions.
   $F-\text{ score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$
5. Response time: It is characterized by the time taken to determine the class of an event by each classification algorithm.

The results of the proposed classification model have been compared with other sophisticated prediction models, primarily Random forest (RF), k-Nearest Neighbor (K-NN), Support Vector Machine (SVM), and the conventional Artificial Neural Network (cANN) to validate the proposed system.

1. Fig. 6(a) depicts the graphical representation of the accuracy of the proposed model in comparison to other models. In this case, the proposed model acquires an average accuracy of 82.28%. In comparison to this, RF achieves 79.25%, k-NN acquires 77.85 %, SVM was able to register 67 % and cANN predicts 79.85 % of attributes results correctly. Henceforth, the proposed classifier is comparatively effective in the accurate determination of COVID-19 results.
2. Fig. 6(b) shows the specificity values calculated for the proposed model in contrast with other states of the art prediction models. From the figure, it can be concluded that over 14 days and continuous feeding of inputs to the models, the proposed model acquires an average precision of 91.42 %. On the other hand, the RF, cANN, k-NN, and SVM models were able to acquire mean specificity of 82.5 % 83 %, 80.42 % and 77 % respectively. Moreover, as the number of days increased, the specificity of the proposed model is also increased, therefore depicting better performance.
3. Fig. 6(c) shows the sensitivity analysis of the proposed model. Numerically, the proposed model acquires maximal sensitivity value as compared to other models with an average of 90 %. On the other hand, other predictive models show comparatively low output.

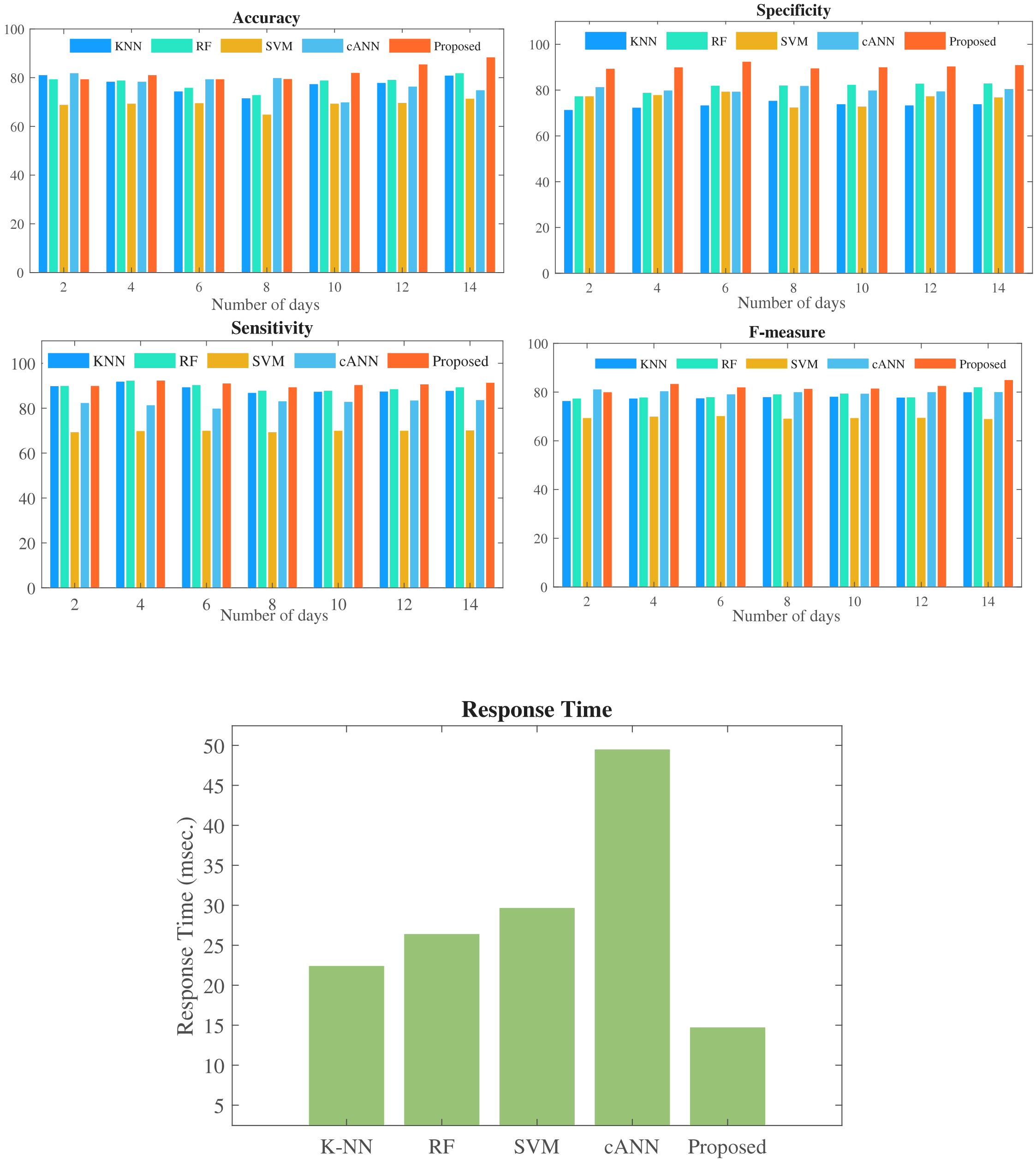

Fig. 6. Comparative analysis with state-of-the-art models. (a) Classification Accuracy (b) Specificity (c) Sensitivity (d) F-measure (e) Response time.

4. F-measure is also computed for the proposed system due to its statistical importance. Fig. 6 (d) shows the graphical values obtained for the f-measure for 14 days. The proposed model shows consistency in f-measure results with an average value of 85.66%.
5. Fig. 6(e) shows the graphical results of each classifier's average response time for giving input for the predefined COVID-19 symptoms defining attributes. From Fig. 6(e), we also conclude that the proposed model has a minimum average response time of 14.79 msec as compared to other predictive models. Based on the results, we can conclude that the proposed model is statistically better in terms of performance when predicting the COVID-19 symptoms results.

3.4. Correlation analysis

Correlation analysis is the measure that is used to test the relationship between categorical variables. It is an important measure to determine the analogous behavior of the model with the real-time results of the proposed model. Two parameters are determined to

Fig. 7. (a) GPS-based routing from A to B. (b) Default routing when location and user mapped. (c) New routing after identification of risk-prone regions.

validate the proposed model authenticity, namely Correlation coefficient (τ) and Kendell rank coefficient (κ). Correlation coefficient (τ) between variable x and y can be computed using $\tau = \frac{\text{cov}(x,y)}{\partial_x \partial_y}$, here cov (x, y) is covariance. Similarly, predicted results are compared with actual obtained results using Kendell rank coefficient (κ).

$$(\kappa) = \frac{X - Y}{\sqrt{\frac{n(n-1)}{2} - X}\sqrt{\frac{n(n-1)}{2} - Y}} \tag{11}$$

Where $X = \sum_x x(x-1)/2$, $Y = \sum_y y(y-1)/2$ Here, n is the parameters of data to be analyzed. Based on these formulas, the acquired results for different prediction models are shown in Table 11. Moreover, the confidence interval for prediction is fixed at 95% with a normalized coefficient of 1.9. From the reference range set for different attributes in Table 11, the proposed model registers maximum correlation ($\tau = 0.64 \pm 0.08$) with respect to actual results as compared to K-NN ($\tau = 0.45 \pm 0.07$), cANN ($\tau = 0.53 \pm 0.09$), SVM ($\tau = 0.51 \pm 0.06$), and RF ($\tau = 0.48 \pm 0.08$) prediction models. Moreover, Kendell rank coefficient (κ) is maximal for the proposed technique as compared to other state-of-the-art techniques. Henceforth, it can be inferred that the proposed methodology is much more precise and efficient than other predictive techniques.

3.5. SNA graph based COVID-19 outbreak prevention

The SNA graph is generated using a net logo [34]. Data about infected COVID-19 patients and locations are generated in Jammu city of India to produce SNA-based graph risk assessments and infected regions. The reports of 5000 users and their locations of travel are stored in two .csv files in the format of a hexagonal structure in the geographic region of Jammu city, as shown in Fig. 7. Moreover, Fig. 7(b) depicts without precautions the routing of the user from path A to B. To minimize the spread and outbreak of COVID-19, the user must pass through non-infected or risk-free regions. Based on the results, the user must be directed to follow a safe route or path using an appropriate rerouting green zone-based algorithm, a demo is shown in Fig. 7(c).

3.6. System stability

In our proposed framework, the system stability has been evaluated because of the increasing number of days required for continuous monitoring of the patients. System stability is practically measured as a result of Mean Absolute Shift (MAS). System stability is defined based on the result provided by the system within a short period as the number of available datasets increases. In the present framework, whenever the system encompasses a significant number of days of high MAS values (above 0.5) the system stability is low, and vice versa. Fig. 8, indicates the results obtained for stability measurements. The MAS value (averaging 0.2409) indicates that the system remains stable even if the number of days is raised and hence highly effective.

4. Comparative analysis

In this section, a comparative analysis of the presented work with the recent studies on diagnosis and monitoring of COVID-19 has been carried out to verify the efficiency. The comparative analysis has been presented in Table 12. From Table 12, it is clear that the proposed methodology is novel and performs better from all evaluation aspects.

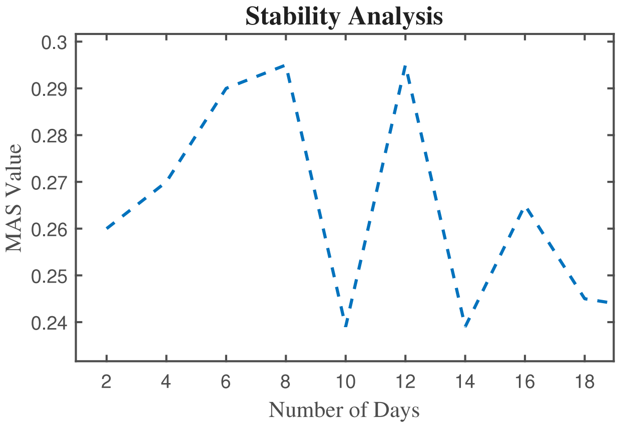

Fig. 8. Overall system stability.

Table 12
Comparison between state-of-the-art methods.

Ref.	Year	Technique	Challenges addressed	Remarks
[35]	2022	CNN-LSTM hybrid model	Solution for economic and social prosperity	Prediction and current status of medical resource availability
[36]	2022	Harris Hawks Optimization and Feature Analysis Using SHAP	Real-time prediction of COVID-19	Presented a ML framework to predict COVID-19.
[37]	2022	EAMA, a multimodel machine learning technique	Prediction of COVID-19 based on different aspects	Long-term prediction compared to other models.
[38]	2021	Support vector machine, Multi-layer perceptron	Short-term forecasting of COVID-19 cases	Presented a model for the forecasting of COVID-19 cases using ML models. SVM outperformed other classifiers with the highest accuracy and minimal root mean square error.
[39]	2021	Convolutional neural networks (CNN), Texture analysis methods	COVID-19 detection using texture-analysis CT-scanned lung images	The results achieved were better compared to the existing studies.
[40]	2021	Convolutional neural network; Deep transfer learning	Automatic coronavirus pneumonia detection using X-ray images	Proposed five algorithms namely, ResNet50, ResNet101, ResNet152, InceptionV3 and Inception-ResNetV2 for prevention of pneumonia associated with coronavirus.
[41]	2021	Decision tree, Random Forest, Support vector machine and neural networks	Predictive analysis using machine learning	Results better for decision tree and random forest in terms of specificity, sensitivity, and area under the curve.
[42]	2021	Enhanced KNN classifier, feature selection	Predictive analysis using machine learning	Introduced an enhanced KNN classifier with feature selection for IoT-based COVID identification.
[43]	2021	Federated Learning	Chest X-ray images for prediction	Performance evaluated in terms of prediction accuracy and loss with high-performance time.
[44]	2020	Multichannel exponent moments, Manta-Ray Foraging Optimization	COVID-19 diagnosis using two datasets on X-rays	Accuracy achieved above 95%.
[45]	2020	Logistic regression based classification technique	Ventilation need among COVID-19 patients	The proposed methodology resulted in minimizing the false positive rate with high sensitivity (0.90) and specificity (0.58).

5. Conclusion and future work

COVID-19 is an acute severe respiratory syndrome that causes lung inflammation and may lead to critical health issues, if not detected and treated early. Moreover, it is an infectious disease that can be transmitted to another person through coughing or sneezing, and physical contact. To mitigate the spread of COVID-19, the recent advances in Industry 4.0 technologies can be used as an effective solution. The fog–cloud-based MCPS not only diagnoses the symptoms of COVID-19 at an early stage but also provides effective information so that efficient decisions can be taken to control this life-threatening disease for further spread. Additionally, in the event of chaos around the world, the use of novel computing techniques such as SNA indicators is a top priority for real-time decision-making. In this paper, an MCPS framework for early detection and efficient decision-making of COVID-19 cases using fog–cloud computing and social network analysis is presented. The fog layer uses PCA to reduce the dimensionality of the data and then classifies it at the gateway to provide immediate results without any delay. The Ensemble learning-based classification technique classifies events and provides information about the severity of COVID-19, and then generates real-time alerts. Social network analysis-based services are used in the cloud layer for preventing the further spread of the disease. The outcomes of the adoption of the proposed methodology show the efficacy of diagnosed COVID-19 cases and their stability over a wide time span. Besides that, suggestions and an alarm generation mechanism enhance the novelty of the proposed system. In the future, the capabilities of the presented methodology will be enhanced by considering various security aspects associated with the transmission and storage of patient data. Moreover, the utilization of related features from the patient's electronic medical records for efficient data analysis and decision-making may also be explored.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The availability link of data sets from different sources is shown in Table 9.

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