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A fog assisted intelligent framework based on cyber physical system for safe evacuation in panic situations

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A B S T R A C T

In the current scenario of the COVID-19 pandemic and worldwide health emergency, one of the major challenges is to identify and predict the panic health of persons. The management of panic health and on-time evacuation prevents COVID-19 infection incidences in educational institutions and public places. Therefore, a system is required to predict the infection and suggests a safe evacuation path to people that control panic scenarios with mortality. In this paper, a fog-assisted cyber physical system is introduced to control panic attacks and COVID-19 infection risk in public places. The proposed model uses the concept of physical and cyber space. The physical space helps in real time data collection and transmission of the alert generation to the stakeholders. Cyberspace consists of two spaces, fog space, and cloud-space. The fog-space facilitates cyber space. The physical space helps in real time data collection and transmission of the alert generation to the stakeholders. Cyberspace consists of two spaces, fog space, and cloud-space. The fog-space facilitates panic health and COVID-19 symptoms determination with alert generation for risk-affected areas. Cloud space monitors and predicts the person’s panic health and symptoms using the SARIMA model. Furthermore, it also identifies risk-prone regions in the affected place using Geographical Population Analysis. The performance evaluation acknowledges the efficiency related to panic health determination and prediction based on the SARIMA with risks mapping accuracy. The proposed system provides an efficient on time evacuation with priority from risk-affected places that protect people from attacks due to panic and infection caused by COVID-19.

1. Introduction

In the last decade, the world has witnessed several incidences of natural and human disasters, comprising droughts and pandemics. Integration of both and their impacts can be leading to severe economic failure, stress, and malnutrition, mostly in developing countries [1]. These circumstances can be caused by technological accidents, natural hazards, violent intergroup clashes, lack of essential resources, and other main risks to health, life, assets, well-being, and others [2]. The COVID-19 virus is infecting people worldwide, about 3 million patients were infected, and approximately 200 thousand lives have been lost till 28 April 2020 (WHO, 2020) [3]. However, the Pennsylvania Supreme Court included COVID-19 in the natural disaster category [4] and referenced that as the other disaster “substantial damage to property, hardship, suffering or possible loss of life”, the COVID-19 belong to the “same general nature or class as those specifically enumerated”, henceforth it is included in the category of natural disaster in the state. Disasters over the years have directed to extensive devastation of physical infrastructure, an immense amount of health issues, a huge amount of human loss including economical damages [5]. As per reports [6,7], in the last year, natural and human-made disasters are reasoned for approximately “140 billion USD” financial damage and stated approximately 11000 lives. The effect of various traumatic accidents during the disaster on mankind may be considered to the conviction of dread, which rapid effect actual responses and referred to a panic attack in the disaster [8]. The investigative standard of “DSM-V of American Psychiatric Association”[9] states that a panic attack can be considered by the incidence of a minimum of four of the symptoms, such as “accelerated heart rate, breathlessness, chest pain, trembling, feeling of choking, nausea, chills, faintness, dizziness, derealization, sweating, tingling, fear of dying, and fear of losing control”. The studies [10,11] investigated that panic attacks mainly evident through nine most common symptoms, such as “heart rate (98.3%), breathlessness (92.0%), dizziness (96.0%), chest pain (85.0%), sweating (88.0%), trembling (84.0%), chills (84.0%), choking (79.0%) and nausea (83.0%)”. Hence, the panic wellbeing of the human being in traumatic events is decisive for efficient timely evacuation and to keep away from health issues related to panic attacks.

The latest inventions of smartphones and technologies such as fog computing, IoT, and cloud computing offer an effective platform for cyber-physical systems models to address disaster and pandemic

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management. Fog computing provides the concept of processing at the network edges with cloud computing features. Fog nodes are capable of computing and storing data with the support of neighboring edge devices [12]. It also helps to reduce the load of clouds and refer to as mini clouds. In the fog layer, fog nodes provide the ability of computation at the edge devices in the network. The processes or tasks that cannot be processed by them are transferred to the cloud space for further processing. The IoT facility provides control and manages smart devices remotely with the application of the internet. CPS uses fog computing and IoT features that integrate various cyber components such as smartphones, wireless sensors, and network devices. CPS has significant applications in various fields such as healthcare, automatic transportation, industry, and so on [12]. Hence, panic wellbeing of the human being in the disaster is decisive for timely evacuation with effectiveness to keep away from any attacks due to panic and infection caused by COVID-19.

1.1. Difficulties and challenges

In the COVID-19 pandemic, the person’s panic well being is also affected by witnessing different intense conditions. The proper and effective on-time evacuation of such a person can prevent panic attacks and COVID-19 infection chances. Therefore, in this situation, the higher educational institutions and other public places are monitored in real-time. The data of persons related to their panic health and COVID-19 symptoms are acquired and analyzed for the effective on-time evacuation for the affected person depending on the priority. Here, Information and Communication Technologies (ICT) facilitates the latest technologies and platforms to evaluate and analyze the evacuation process from remote places and take action consequently. On the other hand, different limits confine the concept of successful evacuation such as communication architecture and real-time processing. The communication infrastructure, including IoT sensors, must communicate among the fog nodes for computing and transmission purposes. In such a condition, the partial or entire communication failure among the users and the response team may direct to interruption and response errors. The scenario such as COVID-19 pandemic, where the timely decision is played an important role for evacuation and other applications. The evacuation teams and monitoring system have to observe real-time health data of users and may face difficulties to monitor real-time data dynamically that can depreciate the effectiveness of priority evacuation. Furthermore, the evaluation efficiency of the framework depends on the accurate data set of the persons related to panic health and COVID-19 symptoms. In addition, the majority of IoT devices in the physical space function on battery sourced power [13]. Therefore, IoT devices need to be recharged at specific intervals without any failure. The proposed system also has some difficulties and challenges in terms of Internet connectivity, Internet speed, the energy consumption of sensors, limited mobile battery, GPS tracking. The wireless network has a challenging problem related to robustness in failed communication and dynamic environment. In addition, some other constraints are short range and interference occurred due to other wireless devices.

1.2. Motivation and focus

On-time evacuation is critical in disaster management operations, and it is attracting increasing attention from various authorities throughout the world. On-time and priority-based evacuation of people through risky and infected areas may rescue their lives and reduce the devastating effects of traumatic events on a person’s wellbeing [14]. Effective risk evacuation can be achieved through real-time condition consciousness, such as the physical environment, and monitoring persons is essential. It provides an integrated depiction of the risk affected regions to the response team. The development and progression in the technology of sensor devices, wireless communication, and their integration in the IoT have allowed using of smartphones and IoT devices in various fields such as disaster management [15], higher education [16], healthcare [17,18], transportation [19,20], industrial manufacturing [21], and others. Cloud computing offers higher storage and computation facilities to analyze real-time data acquired from smartphones and IoT devices. Furthermore, the integration of fog and cloud computing facilitates computing on cloud platforms, location-based computation, and less dependency on the bandwidth of the network. The arrangement is suitable for real time computations, where fog nodes are placed near to the data source and far away from the cloud server. Hence, an efficient and effective on-time and orderly evacuation system can formulate using these technologies with evacuation challenges.

In this proposed cyber–physical system, Data is collected by sensors and devices in physical systems and evaluated by computing resources in cyber systems [22]. Physical space and cyber space are used in the proposed system. Using a wireless network of smartphones and behavioral sensors, as well as IoT-assisted sensors, physical space aids in the gathering of data comprising different health-related aspects. It sends notifications to the relevant stakeholders, prompting them to take appropriate action. Cyberspace has data analytics layers that contain fog and cloud space. The fog space uses locally retrieved time-sensitive records from physical space and transmits the processed physical space data to cloud servers in the cyber space for remote computing. The fog space assists in the determination of panic health and the creation of alerts in real time. It consists of two layers: synchronization and panic health and COVID-19 symptoms determination. After processing in the fog space, the data is sent to the cloud space for health severity analysis and risk analysis. Health Severity Analysis (HSA) Layer and Risk Mapping Layer (RML) are two layers available in the cloud space. The HSA monitors and forecasts the severity of user’s health based on the SARIMA model. The RML allows GPA to identify high-risk areas and prioritize evacuations based on the estimated health severity of the individuals. RML also applies evacuation maps to real-world scenarios based on the monitored risk routes. Routes of evacuation are recognized using the knowledge of risk regions and health severity. The knowledge of these evacuation routes in the risk region and the evacuation priority of persons in those risk regions offer the response team to act accordingly and plan on time and evacuation based on preference.

1.3. Contributions

The proposed cyber–physical system will have a substantial impact on the healthcare and higher education sectors. It provides: (i) A novel cyber–physical system based architecture for on-time evacuation of people amid panic attacks and the COVID-19 pandemic, (ii) For time-series computational services, the proposed approach employs fog-assisted smartphones and IoT devices, (iii) The most important contribution of this proposed model is the panic health severity analysis based on GPA to recognize the risk regions, (iv) Logistic regression is used to classify persons, and cloud computing is utilized to analyze and transmit alerts.

1.4. Literature review

In this section, the related works are discussed and compared based on the following aspects: Fog Computing, Cloud Computing, Internet of Things, Real-Time Monitoring, Prediction Modeling, Evacuation, and Healthcare. Xu et al. [23] contributed to the Relationship-based personalized evacuation approach and presented a system based on Artificial Potential Field and Artificial Potential Field with Relationship Attraction that provide better convergence rate, less evacuation time, and route length. Karthik and Suja [24] presented WSN based geographic map-oriented route discovery to multiple exits and used two approaches, the Markov decision process, and geographic map-based routing, to discover the shortest route. Bhattacharjee et al. [25]...
presented their work on crowd-sensing-based evacuation maps construction with a smartphone and delay tolerant networks, as well as the suggested method for effectively designing pedestrian maps of risk impacted regions. The Sensor-based machine learning assumption and compression and assessed the efficacy of this technique on several IoT methods with two communication scenarios, alert and constant warning. The proposed approach utilized the characteristics of cloud, real-time monitoring, strategy based evacuation, and data reduction. Singh and Sood [12] proposed the fog-assisted CPS system in the 5G network for various applications based on IoT. The framework uses an optical fog network to facilitate real-time delivery with low delay and high scalability in the 5G network. Sun and Zhang [26] discussed machine learning techniques for analyze the DR among the patients with the EHR records and introduced few treatment techniques. Sharma and Agarwal [27] presented a COVID-19 predictive control and modeling CPS architecture. The predictive control technique is utilized to forecast COVID-19 infection spread based on time and space constraints. The model uses the UPPAA protocol to verify the model and incorporate the polynomial-regression curve-fitting for predicting hotspots of the coronavirus infection. Ghita et al. [28] elaborated the importance of digitalization against the new outbreak (COVID-19) and discussed the pandemic management phases such as prevention, preparedness, control, and responses using digitalization. The potential solution to encounter COVID-19 through digital twins includes AI solutions for sanitary crises, the digital economy, the smart supply chain transition, smart cities, and smart manufacturing. Ro et al. [29] designed a Cyber Physical Systems based on the SEIR model and created different classes of controllers for epidemiology and can be used to prevent the disease in various countries. Santamaria et al. [30] discussed the cognitive intelligence-based human action using behavioral sensors utilizing IoT, fog, cloud computing, and healthcare applications. Asghari et al. [31] presented the prediction of medical situations for providing timely health services using advanced IoT and cloud computing technologies. Most of the papers based on health care that utilized IoT, fog, and cloud computing have focused on health monitoring, predictions of disease, panic health, and COVID-19 pandemic related problems [32,33]. The literature review has not come across a smart healthcare system on panic attacks and COVID-19 infection after analyzed studies and assessing the state-of-the-art works. Henceforth, a cyber–physical system is required that focused on panic health problems during disasters. The main contribution of this proposed framework related to the healthcare and education domains are (i) The person’s panic health and COVID-19 symptoms were determined using fog computing, (ii) A cloud-based monitoring system of panic health and COVID-19 symptoms of persons, (iii) A cloud-based risk mapping and evacuation of the person using GPa. Table 1 shows the the description of symbols and abbreviations used in this paper.

2. Proposed framework

The proposed cyber–physical system for predicting and preventing panic attacks and COVID-19 infection. Fig. 1 depicts the working of the proposed system based on physical space and cyber space. The physical space helps to data acquisition process using different sensors, and the cyberspace facilitates various data analytics. The cyberspace includes two subspaces, fog space and cloud space. Fog space uses fog computing to provide local data analytics that comprises three layers — synchronization layer (SYN), panic health, and COVID-19 symptoms determination layer. In the proposed system, the physical space acquires data from the IoT devices and sensors, fog space process the received data from physical space, and the data is stored in the cloud storage using cloud space. The cloudspace has Health Severity Analysis Layer (HSAL) and Risk Mapping Layer (RML) that analyze health severity and risk mapping by recognizing evacuation maps to real-time situations. Therefore, the evacuation of affected people in those risk areas may be possible using the priority of the person’s health parameters.

| Table 1 Symbol and abbreviation description. |
| Notation | Definition |
| IoT | Internet of Things |
| GPA | Geographical Population Analysis |
| SARIMA | Seasonal Auto Regression Integrated Moving Average |
| ICT | Information and Communication Technologies |
| HSA | Health Severity Analysis |
| RML | Risk Mapping Layer |
| HSAL | Health Severity Analysis Layer |
| GPS | Global Positioning System |
| PHealth | panic health |
| COVSym | COVID-19 symptoms |
| PSCSI | Panic Severity and COVID-19 Symptoms Index |
| PnHk | Panic health record of the user at a particular instance |
| 𝜋₀, 𝜋₁ | Intercept of bias for panic health record |
| 𝛾₀, 𝛾₁ | Intercept of bias for COVID-19 symptoms record |
| 𝜌₀ | Coefficient of panic health record |
| 𝜌₁ | Coefficient of COVID-19 symptoms record |
| PHI | Class of the determined panic health |
| CH | Class of the determined COVID-19 symptoms |

2.1. Physical space

The physical space acquires real-time data related to panic health, a personal record, and COVID-19 symptoms. The system collects lots of data in real-time from the users by mobiles and sensors using the IoT, fog, cloud computing, and the cyberspace. The physical space acquires data from the IoT devices and sensors. This layer is hosted by IoT sensors at higher education institutions and can be used to collect data related to panic health and COVID-19 symptoms. The physical space is connected to the cyberspace through IoT sensors and allows real-time data processing. The physical space includes two subspaces: fog space and cloud space. The fog space uses fog computing to provide local data analytics that comprises three layers — synchronization layer (SYN), panic health, and COVID-19 symptoms determination layer. In this layer, PANID and COVID-19 symptoms data are used to classify the panic health (PHealth) and COVID-19 symptoms (COVSym) of the user, which either belong to the SAFE or UNSAFE class. The SAFE class presents that the user is neither panic nor having COVID-19 symptoms and not required any emergency during the evacuation process from the safe region. The UNSAFE class presents users may be panic or have COVID-19 symptoms, hence requires special attention and medical response and give priorities in the process of evacuation analysis. The two vectors $P_i H_k$ and $C_i S_j$ are formed by Panic health and COVID-19 symptoms data attributes of the user at a particular instance $i$. The panic attack and...
COVID-19 infection incidences are determined in vectors \( (P_nH_k \text{ and } COVS_k) \) using the detection of any three and more symptoms. Hence, the Panic health and COVID-19 infection determination layer use logistic regression for the classification of PHealth and COVSym of the user. Logistic regression is used to explain the association between response attributes and classify categories based on decision boundaries that are defined by a threshold of different situations. Therefore, Logistic regression is suitable to determine the panic health and COVID-19 symptoms of the user. In general, logistic regression classifies data into distinct categories and defines decision boundaries as linear or non-linear. The classification of PHealth and COVSym records based on logistic regression are described in Eqs. (1) and (2) based on the threshold.

\[
\delta = \frac{e^{\alpha_0 + \alpha_1P_nH_k}}{1 + e^{\gamma_0 + \gamma_1P_nH_k}} \quad (1)
\]

\[
\eta = \frac{e^{\alpha_0 + \alpha_1COVS_k}}{1 + e^{\gamma_0 + \gamma_1COVS_k}} \quad (2)
\]

Where \( \delta \) and \( \eta \) are the outputs of logistic regression respectively, \( \alpha_0 \) and \( \alpha_1 \) are the intercept of bias and the Panic Health coefficient respectively, \( \gamma_0 \) and \( \gamma_1 \) are the intercept of bias and the COVID-19 symptoms coefficient respectively, and \( P_nH_k \) and \( COVS_k \) are the Panic Health and COVID-19 Symptoms of the user at \( t_k \) time instance respectively. \( \alpha_0 \) and \( \gamma_0 \) are the coefficients not associated with any input feature and determined by log-odds of the reference variables (the intercepts of bias). \( \alpha_1 \) and \( \gamma_1 \) are the coefficients of the input features (coefficients
of Panic Health and COVID-19 symptoms. As per logistic regression, the response outputs are to be binary (Yes or No) for categorical classification of PHealth and COVSym records. The Bernoulli distribution defines the probabilities of PHealth and COVSym as follows: PHealth = 1 (SAFE), COVSym = 1 (SAFE), if the outputs of the functions are \( \delta \) and \( \eta \) respectively. PHealth = 0 (UNSAFE), COVSym = 0 (UNSAFE), if the outputs of the functions are 1-\( \delta \) and 1-\( \eta \) respectively. The sigmoid function is used by logistic regression to offer classifications the records into given categories based on thresholds of the output of the function as Eqs. (3) and (4) and formed s-shaped curve.

\[
P H = \frac{1}{1 + e^{-\delta}} \quad \text{(3)}
\]

\[
C H = \frac{1}{1 + e^{-\eta}} \quad \text{(4)}
\]

where PH and CH are the classes of the determined Panic Health and COVID-19 Symptoms, respectively. Sig() function presents the where \( PH \) and \( CH \) are the classes of the determined Panic Health

Algorithm 1: Panic Health and COVID-19 Symptoms Determination and Alert Generation

Data : Panic Health Record \( P_H \), COVID19 Symptoms Record \( C_S \), time instance \( t_k \)

Result: PH and CH of the user with health alerts

1 repeat
2 Calculate current time instance \( t_k \)
3 Mapping of \( P_H \) and \( C_S \) to feature space
4 Calculate the PH and CH of the mapped sample as:
5 \[
PH= \text{sig}(\delta) = \frac{1}{1 + e^{-\delta}}, \quad \text{and} \quad CH= \text{sig}(\eta) = \frac{1}{1 + e^{-\eta}}
\]
6 // Where value of \( \delta \) and \( \eta \) are:
7 \[
\delta = \frac{\rho_0 + \rho_1 t_k + \rho_2 \kappa}{\gamma_4}, \quad \text{and} \quad \eta = \frac{\rho_0 + \rho_1 t_k + \rho_2 \kappa}{\gamma_5}
\]
8 Forward Diagnostic alert (PH and CH) to the user
9 if \( (PH==\text{UNSAFE} \quad \text{or} \quad CH==\text{UNSAFE}) \) then
10 | Forward health alert to the user, and stacks-holders
11 Transmit \( P_H \) and \( C_S \) to the Cloud space
12 else
13 | Forward alert to the user regarding safe region
14 end
15 until the user get evacuated
16 END

2.2.2. Cloud space

Cloud storage is a part of cloud space that saves accessible data from fog space in a time-series manner. It is made up of a series of observations that are completed over time. Health severity analysis and risk mapping layers are available in the cloud space.

2.2.2.1. Health severity analysis. The HSA layer analyzes the Panic Health and COVID-19 symptoms time-series records for Panic Health Severity and COVID-19 Symptoms Index (PSCSI) Monitoring and predictions and transmit data to the RML for safe evacuations. Panic Severity and COVID-19 Symptoms Indexes provide a probability measure for identifying the Panic Severity and COVID-19 infection consequences on the users. These indexes facilitate the on-time evacuation of users based on preference. A high-rise in the Panic Severity and COVID-19 Symptoms Indexes present the chances of severe health risk due
to panic attacks and the chance of COVID-19 infection. Hence, the indexes of Panic Severity and COVID-19 Symptoms are monitored and predicted to recognize the unsafe regions, and priorities for evacuation are given to users belonging to these regions. The index monitoring for Panic Severity and COVID-19 Symptoms are prepared using conditional probability. Eq. (5) depicts the index monitoring of HSA.

\[
PSCSI = P \left( \frac{PH \cup CH}{E_1 \cup E_2 \cup \ldots \cup E_k} \right)
\]

where PSCSI represents Panic Severity and COVID-19 Symptoms Index. PH and CH denote the classes of the determined Panic Health and COVID-19 Symptoms, respectively. \( E_k \) presents the occurrence of deleterious events in time instance \( T_k \). Cloud server uses PSCSI during the process of monitoring of Panic Health and COVID-19 Symptoms of users.

The Seasonal Auto Regression Integrated Moving Average (SARIMA) technique is used to predict PSCSI at the HSA layer. The prediction model SARIMA is the expansion of the Autoregressive Integrated Moving Average (ARIMA) that is used to predict time-series data. In this model, prediction accuracy can get better by eliminating seasonal deviation features during seasonal differences. In general, traditional time series models such as ARIMA and SARIMA models are used in epidemic time series forecasting. The SARIMA method merges seasonal differencing factors with ARIMA for effective time-series data modeling applications with periodic features. Therefore, the SARIMA prediction model is used to identifying the structure and pattern of linear data in the proposed framework. As the proposed model deals with real time data, the solution is dynamic in nature due to the movement of the user from one place to another. The SARIMA prediction model is used to predict PSCSI at the HSA layer to predict time-series data dynamically. Aside from classical time-series forecasting, new advances in deep learning for time series prediction, Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM) have received a lot of attention. In addition, Deep learning methods In time series forecasting, RNN and LSTM algorithms can identify data patterns including non-linear property and complexity.

In the proposed model, panic attacks and COVID-19 infections are directly related to the population density of users and their health attributes value. In this context, SARIMA model improves the efficiency of the prediction of a future panic attack and COVID-19 infection. Hence, the HSA layer used the SARIMA prediction model for predicting the PSCSI. The SARIMA model expands ARIMA with the inclusion of additional hyper-parameters as seasonal characteristics of the record. The SARIMA model contains the “seasonal autoregressive term (A)”, “the seasonal integrated term (D)”, and “seasonal moving average term (M)”, together with the “autoregressive term (a)”, “the integrated term (d)”, and “moving average term (m)”. The model is represent as

\[
\phi_d(L)\phi_s(L^k)\phi_s(L^R)\left[1 - L^d\left(1 - L^R\right)^k\right]Z_k = \theta_d(L)\theta_s(L^k)\theta_s(L^R)\theta_s(L^R)W_k
\]

and,

\[
\phi_d(L) = 1 - \phi_1L^2 - \phi_2L^2 - \ldots - \phi_pL^p
\]

\[
\theta_d(L) = 1 - \theta_1L^2 - \theta_2L^2 - \ldots - \theta_mL^m
\]

\[
\phi_s(L^R) = 1 - \phi_{1R}L^R - \phi_{2R}L^R - \ldots - \phi_{pR}L^{pR}
\]

\[
\theta_s(L^R) = 1 - \theta_{1R}L^R - \theta_{2R}L^R - \ldots - \theta_{mR}L^{mR}
\]

Here \( \Phi \) and \( \Theta \) represent coefficients of “seasonal autoregression” and “seasonal moving average”. Similarly, \( \phi \) and \( \theta \) represent coefficients of “autoregression and moving average”, \( A \) and \( M \) are the order of seasonal autoregression and seasonal moving average terms, respectively. The order of “non-seasonal autoregression” and “non-seasonal moving average” terms are represented by \( a \) and \( m \). \( D \) represents the differencing order, and \( R \) is the seasonality length. \( \epsilon_k \) presents the random error at time \( k \). In addition, The random error \( \epsilon_k \) follows a unique normal distribution with a mean of zero. The SARIMA approach is also
appropriate for the short-term as a contrast to long-term prediction as it offers high-weights to the latest data [37,38].

The prediction of Panic Severity and COVID-19 Symptoms Indexes based on the SARIMA model, it contains four stages: (a) identification of stationarity, (b) recognition and estimation of parameters, (c) Model diagnosis, (d) Prediction. In the first stage, the stationary data is identified and determine the order of non-seasonal difference d and seasonal difference D. The value of a, A, m, and M are also identified using Partial Autocorrelation and Autocorrelation Functions. The second stage is used to estimate corresponding standard errors and parameters using square lease estimation, Yule–Walker, and maximum likelihood measures. The third stage is used to evaluate different models and analyzed their residuals. The model with the least residual or “Mean square error”, “Root mean square error” and “Mean absolute error” is chosen. The selected model predicts the Panic Severity and COVID-19 Symptoms Indexes in the last stage, as described in Algorithm 2. The predicted PSCSI of users is transferred to the RML to identify critical sections, and evacuation can be done based on priority in those regions.

**Algorithm 2: Panic Severity and COVID-19 Symptoms Indexes**

| Data: Monitored PSCSI Time-series record | Result: Predicted PSCSI |
|-----------------------------------------|-------------------------|
| 1 Identify the differencing order for stationarity. |  |
| 2 Investigate Plots of ACF/PACF to choose the composition of SARIMA method. |  |
| 3 Discover “non-seasonal” and “seasonal autoregressive” and “moving average terms”. |  |
| 4 Choose the model with minimized errors. |  |
| 5 Predict the PSCSI at \( k^{th} \) time occurrence based on the preferred model. |  |
| 6 END |  |

2.2.2.2. Risk mapping layer. To reduce the chance of COVID-19 infection in higher educational institutions and public places, the requirement of an effective evacuation process is necessary. In this situation, the convergence of evacuation maps with real conditions, the discovery of critical places, and ordering of the evacuation of the witnessed user due to COVID-19 symptoms of self and others in critical places can facilitate the timely evacuation based on priority. Therefore, this layer analyzes the panic and COVID-19 symptoms information to converse the COVID-19 prevention and evacuation maps to the real condition of the region. This layer offers PSCSI time series records to recognize the unsafe areas and define evacuation priorities for the users in that places. The COVID-19 symptoms are analyzed by this layer and determine whether the location is safe or unsafe based on their threshold. The threshold values have been selected and modified on the equal distribution of PSCSI values to categorized people based on the panic health and COVID-19 symptom. This layer also analyzed the PSCSI time-series data for identification of the peak health severity of users, critical regions and priority of evacuations in the future.

In the RML, the critical regions are identified using GPA based on the determined highest PSCSI of the users. Table 5 depicts the classification of PSCSI based on GPA. Here GPA classifies the user population depending on their calculated PSCSI in to four classes – Strong (PSCSI \( \geq 0.86 \)), Moderate (0.58 \( \leq \) PSCSI \( < 0.86 \)), Mild (0.30 \( \leq \) PSCSI \( < 0.58 \)), and None (None \( < 0.30 \)) and priority weights of evacuation. The higher PSCSI value has the top priority of evacuation. The risk associated with a region (safe or unsafe) is determined by the population density of the area, as discussed in Table 6. In table, the regions are categorized based on the population density of various users node such as (i) Category high (red color) having more than 20 maroon nodes, i.e. population of the strong class is more than 20, high chance of panic attack, (ii) category medium (orange) having D(Red node) \( \geq 30 \) AND D(Maroon node) \( < 20 \) AND D(Blue node)\( < 50 \), (iii) category low (Yellow) D(Blue node) \( \geq 50 \) AND D(Maroon node) \( < 20 \) AND D(Blue node) \( < 30 \), (iv) category safe (green) D(Green node) = 100, i.e. PSCSI value of the population is less than 0.30, (v) category none (white) having no population.

GPA classifies risk affected regions into hexagonal areas and depicts the direction of the safe evacuation of various population density in Fig. 2 based on the description in Table 6. The different risk regions are recognized by analyzing the density of the population of the PSCSI classified user in those regions. The region priority (\( Reg_{Pri} \)) is defined as

\[
Reg_{Pri} = \int_{r=1}^{4} PrWt_r \times d
\]

where, \( PrWt_r \) is the priority weight of evacuation of the respective category population, and \( d \) denotes the share of the population of a particular region \( r \). The definite integral is considered precisely the limit and summation used to find the net area. In the definite integral, if a non-negative velocity function is used for an item traveling down an axis, the region in the velocity function involving the lower and higher limits indicates how far the object moved during that time interval. Algorithm 3 represents the overall working of the RML of the proposed model.

### Table 5

| S.No | Category | PSCSI value | User node color | PrWt |
|------|----------|-------------|----------------|------|
| 1    | Strong   | \( \geq 0.86 \) | Maroon         | 4    |
| 2    | Moderate | 0.58 \( \leq \) PSCSI \( < 0.86 \) | Red           | 3    |
| 3    | Mild     | 0.30 \( \leq \) PSCSI \( < 0.58 \) | Blue          | 2    |
| 4    | None     | PSCSI \( < 0.30 \) | Green         | 1    |

AND D(Red node) \( < 30 \), (iv) category safe (green) D(Green node) = 100, i.e. PSCSI value of the population is less than 0.30, (v) category none (white) having no population.

3. Performance assessment

The Performance Evaluation of the proposed Cyber–Physical System contains section four subsections — Data set for the experiment, Panic Health determination, panic severity prediction evaluation, and risk mapping efficiency.

3.1. Data set and simulation tools

As there is a non-availability of accurate data set of risk-oriented evacuation, a synthetic data set is created through referring datasets [39] with the consultation of various doctors, pathologists and academician of this domain, and 8400 records are created for their panic health determination during the pandemic of COVID-19. The CupCarbon is used for simulation of deployed IoT sensors in the higher educational institutions or public places. In the CupCarbon platform, the sensors provide random values of panic status to facilitate real-time scenarios and mapped the users’ health records to simulate the higher education institution scenario. In the CupCarbon platform, the sensors provide random values of panic status to facilitate real-time scenarios and mapped the users’ health records to simulate the place scenario. It also offers a dynamic configuration of the sensor nodes. In the CupCarbon tool, SenScript is used for real-time coding, which configures each mobile and sensor node individually. The simulation parameters used by SenScript are Standards, Simulation time, Simulation radius, Initial energy, and Simulation time. In addition, Java API is used to highlights the risk region and locate the risk status, either safe or unsafe. PSSCI class of users and region priorities is used to ensure proper on-time evacuations based on priority in particular risk regions.

AND D(Blue node) \( < 30 \), (iv) category safe (green) D(Green node) = 100, i.e. PSCSI value of the population is less than 0.30, (v) category none (white) having no population.
### Table 6

| S.No. | Category | Population density of area (%) | Region color |
|-------|----------|-------------------------------|--------------|
| 1     | High     | \(D(\text{Maroon\_node}) \geq 20\) | Red          |
| 2     | Medium   | \(D(\text{Red\_node}) \geq 30\) AND \(D(\text{Maroon\_node}) < 20\) AND \(D(\text{Blue\_node}) < 50\) | Orange       |
| 3     | Low      | \(D(\text{Blue\_node}) \geq 50\) AND \(D(\text{Maroon\_node}) < 20\) AND \(D(\text{Red\_node}) < 30\) | Yellow       |
| 4     | Safe     | \(D(\text{Green\_node}) = 100\) | Green        |
| 5     | Blank    | No population                 | No Color     |

#### Algorithm 3: Risk Mapping

**Data**: PSCSI time series based data, temporal data, current instance \(t_k\), and range \(r\)

**Result**: Risk evacuation map and critical regions

```plaintext
for Each time instance \(t_k\) do
  for Each deployed IoT sensors \(s_k\) do
    if RiskValue > threshold value then
      if Location(\(s_k\)) is highlighted then
        go to step 2
      end
    else
      Highlights(\(s_k\))
    end
  end
  else
    if location(\(s_k\)) is highlighted then
      Unhighlight(\(s_k\))
    end
  end
end
for Each location of the users do
  Spot the position of the user with node
  Evaluate the highest PSCSI in a future by,
  \[ PSCSI_k = \text{highestPSCSI}(t_k, t_{k+r}) \]
  Paint the Node based on the Colors defined in Table 5
  Determine the priority of Evacuation using,
  \[ EvacPri_k = \text{PSCSI}_k \]
end
for Every \(j^{th}\) region of the panic identified areas do
  Identify population density of different color nodes
  Paint the region with color defined in Table 6
  Evaluate the region priority using,
  \[ \text{RegPri}^{(d)} = \sum_{j=1}^{d} PrW(T_j) \]
end
```

#### 3.2. Evaluation of panic health determination

In the HSA layer, panic health is locally determined by IoT devices using close approximation. It uses logistic regression for the classification of panic health as SAFE or UNSAFE. The classification performance is measured using statistical measures, such as “accuracy”, “F-Measure”, “sensitivity”, and “specificity”, to evaluate logistic regression performance with Decision Tree, k-Means Clustering, and Naive Bayes approach. The accuracy refers to the precision of the classification model, which is used to classify the Panic health and COVID-19 symptoms records. This performance metric is used to identifying the classification model, and with the help of this classification model, PH and CH classes of the panic health and COVID-19 symptoms are determined. Fig. 3(a) depicts the comparison of classification performance, and it is observed that the logistic regression has the highest accuracy of 98.42% in comparison of Decision Tree (97.89%), k-Means Clustering (72.36%), and Naive Bayes (97.1%). The logistic regression also has the maximum sensitivity (99.40%), specificity (99.20%), and F-measure (99.74%). Therefore, the logistic regression approach of classification is very efficient for the panic health classification of the user. It is also analyzed that the logistic regression takes less time for classification than other approaches during panic health determination. Fig. 3(b) shows the efficiency of the classifier based on classification time and depicts the potential of the logistic regression approach, which is used to generate alerts to the user and other stack holders in the fog layer.

#### 3.3. Evaluation of panic severity prediction

The cloud space predicts PSCSI based on health and environment data, including the location of users using the SARIMA model. Also, it receives records with geographical details, location, and sensors status. The prediction evaluation uses the SARIMA model in R Studio with the hardware support of the Amazon EC2 virtual machine. Autocorrelation function and partial autocorrelation function scheme are utilized to establish an accurate model of SARIMA[40]. Fig. 4 presents the evaluation of Panic severity prediction for a particular time window. The prediction of PSCSI is based on panic wellbeing and COVID-19 symptoms of users. It depicts the prediction of PSCSI values of users in the time window. The time window is updated in regular intervals. The effectiveness of the SARIMA model is assessed using PCA and SVD methods. It is observed that the comparison of the SARIMA model with the PCA and SVD approach reveals that the PCA based SARIMA has less
error and high performance as compared to the SVD method. The two most common metrics, "Mean Squared Error (MSE)" and "Root MEAN SQUARED ERROR (RMSE)", are utilized to compute the accuracy of the SARIMA model. SARIMA with PCA approach has an MAE value of 0.1412 and RMSE value of 0.5602 less error, where SVD approach has MAE and RMSE values 0.3565 and 0.8427, respectively. The result analysis of these metrics indicates that the SARIMA with PCA method has less error and high accuracy in this framework.

### 3.4. Risk mapping efficiency

The Risk mapping layer (RML) constructs an evacuation map by identifying critical regions based on risk status received from sensors using GPA of the person. The hexagonal shape is used to present region as the hexagon shape is the ideal way to partition the plane into equal areas, the Sensors are placed at the center of hexagon for optimize the sensor frequency as well as to cover entire area. Fig. 5(a) highlights the risk region by Java API to locate the risk status, either safe or unsafe. PSSCI class of users and region priorities are used to ensure proper on-time evacuations based on priority in particular risk regions. Fig. 5(b) represents the evacuation map, and Fig. 5(c) shows well depicted risk regions, where red color hexagon presents the highest priority of evacuation, followed by orange, yellow, and green color. In this system, multiple scenes have been analyzed and the stable case (in Fig. 5) has been taken and presented. The distribution of region color in mapping is based on the PSCSI value and the area density. The risk regions are assigned a specific color to represent the severity level of risk, such as red, orange, yellow, and green color, representing high-risk, medium risk, low-risk, and safe areas, respectively. A region with no color depicted no population in the respective area. A well-depicted result of the evaluation of risk mapping is shown in Fig. 5. As a result, depending on the person’s panic health and COVID-19 symptoms, the RML provides a well efficient, on-time, and priority evacuation.

In the proposed system, users get an evacuation map based on their well-being (health data), their PSCSI values, and population density. This map can be used (i) for the safe and priority-based timely evacuation of users that have symptoms of a panic attack or COVID-19, (ii) to suggest a safe evacuation path to users so that they do not get panic or infected. In case of priority-based timely evacuation of the users that have higher PSCSI values (higher symptoms of a panic attack and COVID-19), the proposed system sends alerts to users and stakeholders to take necessary action regarding quarantine or hospitalization for further diagnosis, so that dissemination of infection can reduce and hence the other persons are unaffected from infection. The proposed system also offers an evacuation map to safe users that have fewer or no symptoms of a panic attack and COVID-19 (hold low PSCSI values), and the risk associated with the region is determined by the population density of people and their PSCSI values (as per Tables 5 and 6). In case most of the people moved to the safe region, they remain safe due to they hold very less PSCSI values (fewer or no symptoms) in that particular region. Moreover, if any person is found with a higher PSCSI value, the system sends an alert to the person as well as stakeholders to on-time safe evacuation from that region for isolation of that user or hospitalization for further diagnosis. Therefore, other people in that region do not get panic or infected, this way we can control the dissemination and maintain the wellbeing of people.

### 4. Conclusion

In this paper, a fog-assisted cyber–physical system has been proposed for safe evacuations of persons based on priority to save them from panic attacks in this COVID-19 pandemic. The proposed model used smartphones and IoT devices for time-series computational services at fog space. The main contribution of this proposed model is the panic health severity analysis based on GPA to recognize the risk regions for safe on time evacuations. Logistic regression is employed to determine the panic health and COVID-19 symptoms of the user as it has the highest accuracy as compared to Decision Tree, k-Means, and Naive Bayes. Cloud computing is utilized to analyze and transmit health alerts effectively. The performance evaluation of the proposed model implemented on Amazon EC2 cloud and it acknowledged the efficiency of panic health and COVID-19 symptoms determination, prediction of the SARIMA model, and identifying risk region using GPA. The proposed model has effectively dealt with the evacuation map in the different categories of regions to control panic attacks and offered the on-time panic evacuation based on priority. The outcome of this paper helps people to avoid region-based exposure of infection and provide a platform to design a system for effective management for panic prevention.
CRediT authorship contribution statement

Sandeep Kumar Sood: Conceptualization, Methodology, Validation, Resources, Data curation, Writing – review & editing.
Keshav Singh Rawat: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – review & editing, Visualization.

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.

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