Fog-assisted Energy Efficient Cyber Physical System for Panic-based Evacuation during Disasters

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Disasters around the world have adversely affected every aspect of life and panic-health of stranded persons is one such category. An effective and on-time evacuation from disaster-affected areas can avoid any panic-related health problems of the stranded persons. Although the nature of disasters differ in terms of how they occur, the evacuation of stranded persons faces approximately same set of issues related to the communication, time-sensitive computation and energy efficiency of the devices operated in the disaster-affected areas. In this paper, a cyber physical system (CPS) is proposed that takes into account various challenges of the disaster evacuation, so an efficient on-time and orderly evacuation of stranded panicked persons could be realized. The system employs fog-assisted mobile and UAV devices for time-sensitive computation services, data relaying and energy-aware computation. The system uses a fog-assisted two-factor energy-aware computation approach using data reduction, which enables the energy-efficient data reception and transmission (DRecTrans) operations at the fog nodes and compensates to extend the period for other functionalities. The data reduction at fog devices employs Novel Events Identification (NEI) and Principal Component Analysis (PCA) for detecting consecutive duplicate traffic and data summarization of high dimensional data, respectively. The proposed system operates in two spaces: physical and cyber. Physical space facilitates real-world data acquisition and information sharing with the concerned stakeholders (stranded persons, evacuation teams and medical professionals). The cyber space houses various data-analytics layers and comprises of two subspaces: fog and cloud. The fog space helps in providing real-time panic-health diagnostic and alert services and enables the optimized energy consumption of devices operate in disaster-affected areas, whereas the cloud space facilitates the monitoring and prediction of panic severity of the stranded persons, using a conditional probabilistic model and seasonal auto regression integrated moving average (SARIMA), respectively. Cloud space also facilitates the disaster mapping for converging the evacuation map to the actual situation of the disaster-affected area, and geographical population analysis (GPA) for the identification of the panic severity-based critical regions. The performance evaluation of the proposed CPS acknowledges its Logistic Regression-based panic-well being determination and real-time alert generation efficiency. The simulated implementation of NEI and PCA depicts the fog-assisted energy efficiency of the DRecTrans operations of the fog nodes. The performance evaluation of the proposed CPS also acknowledges the prediction efficiency of the SARIMA and disaster mapping accuracy through GPA. The proposed system also discusses a case study related to the pandemic disaster of coronavirus disease 2019 (COVID-19), where the system can help in panic-based selective testing of the persons, and preventing panic due to distressing period of COVID-19 outbreak.

Keywords: Fog Computing; Panic Attacks; Unmanned Aerial Vehicle (UAV); Energy Efficiency; Logistic Regression; Principal Component Analysis (PCA); Seasonal Auto Regression Integrated Moving Average
1. INTRODUCTION

Disasters over the past several decades have led to considerable destruction of physical infrastructure, a massive amount of human injuries, large-scale human causalities and substantial economic losses [1,2]. According to Swiss Re Institute [3], the natural and manmade disasters in 2019 have jointly caused around 140 billion USD economic losses and claimed more than 11 000 lives. The Indian floods during the month of August in 2019 have killed more than 420 persons and caused an economic loss of 7 billion USD [4]. Alone the disaster of wildfires in 2015 has victimized 494 000 persons and caused a 3.1 billion USD economic damage [5]. The hurricane Katrina in 2005 has affected millions of people and killed more than 1800, and caused 340 billion USD economical loss [6]. Such substantial increase in number and impact of disasters in the recent past has affected every corner of the world, and made disaster-associated risks the significant part of the threat-space on this planet [7]. The disaster-associated risks can be mapped from the exacerbating effects of the climate change [8], and deteriorating situations like unplanned urbanization, demographic changes and unpreparedness to deal with disaster events [9]. Resultantly, the human population exposure to disasters has increased significantly [10] and posing various threats to the entire humankind. One such threat is panic-related health problems.

The exposure to potentially traumatic events like disasters has severe consequences in various health-related issues, and this can be attributed from the extensive literature, which indicates that the high incidence of panic attacks (69–77%) occurs among the persons exposed to traumatic events and causes various panic-related health problems [11] [12]. The impact of witnessing various traumatic events during disasters, on stranded persons, can be characterized by the feeling of fear, which prompt stern physical reactions known as panic in disasters [13]. These incidences of panic occurred in the form of sudden periods of intense fear termed as panic attacks. The sudden onset of a panic attack without any warning causes intense discomfort [14] [15], and typically spans over 10 to 20 min, but may last for more than an hour in extreme cases [16]. The diagnostic criteria of DSM-V of American Psychiatric Association [17] state that a panic attack can be characterized by the occurrence of at least four of the symptoms, namely accelerated heart rate, breathlessness, chest pain, trembling, feeling of choking, abdominal discomfort or nausea, chills or feeling of warmth, insatiability or faintness, dizziness, derealization or feeling unreal, sweating, hallucinations or numbness or tingling, fear of dying and fear of losing control or oncoming madness, whereas a clinical study [18] has found that the prevalence of panic attack is majorly manifested by the nine most commonly endorsed symptoms, namely accelerated heart rate (98.3%), dizziness (96.0%), breathlessness (92.0%), sweating (88.0%), chest pain (85.0%), chills (84.0%), trembling (84.0%), nausea (83.0%) and choking (79.0%).

Panic-exposed situations can lead to the various medical conditions [19] among persons viz. panic disorder, post-traumatic stress disorder (PTSD), effect on cardiovascular system and impairment of immune system. In panic disorder [20], the panic attacks occur repeatedly and unexpectedly, and the person remains in a constant terror of having additional occurrences of panic attacks. In PTSD [21], lasting consequences of traumatic ordeals viz. helplessness, intense fear etc. develop and remain for months. The long-term panic exposure can affect the human body, and increase the susceptibility of developing chronic medical conditions [22]. In a situation of panic, stress or anxiety, the brain sends signals to fight or flee in response. The body responds by releasing hormones like cortisol. However, the long-term exposure of cortisol impairs the immune system, as cortisol prevents the release of chemicals which causes inflammation, which consequently affects the capability of the immune system to protect the body against infections. That’s why persons with the chronic condition of panic disorder may be likely more susceptible to catch flu, common cold or other kinds of infections. In a situation of panic, breathing may become shallow and rapid, a situation called hyperventilation, where the body allows lungs to inhale more oxygen, so the oxygen could transport in the body quickly, and prepare the body to respond to the situation of panic. The situation may become worse for a person suffering from Chronic Obstructive Pulmonary Disease (COPD). Panic situations can also accelerate the heart rate. A person suffering from vasoconstriction (a medical condition, where the blood vessels of the person are narrow) may experience increased vulnerability of coronary events, in a situation of panic. Henceforth, the consideration of panic health of the stranded persons during the disaster is critical for on-time and effective evacuation, and to avoid any panic-related post-disaster health problems.

1.1. Challenges

During disasters, the panic-health of the stranded persons is impacted due to the witnessing of various dreadful situations. The evacuation of such persons on a priority basis can prevent
the ill-effects of panic on their health. However, the situations of critical infrastructure like roads, bridges, buildings etc., in the disaster-affected areas, change over the time due to the disruptions and dynamic phenomenon like the flooding of roads, smoke, debris, etc. Hence, in such situations, the real-time monitoring and analysis of the stranded persons’ health and situational information of the disaster-affected areas can enable the evacuation process effective and timely [23]. This can be only possible if the Information and Communication Technologies (ICT) could complement the evacuation teams in realizing the entire situation from remote locations, and enable them to act accordingly.

However, the various limitations restrict the realization of the effective evacuation process: (1) communication, (2) time-sensitive computation and (3) energy efficiency of the devices, in disaster-affected areas. Communication is one of the main concerns in disaster-affected areas. The communication infrastructure is highly affected by the destructive nature of the disasters, and most of the time leads to the complete breakdown of the entire communication network [24]. In such situations, the partial or complete failure of communication between the stranded persons and response system can lead to the delays and faults in response and subsequently to unavoidable loss of life. In situations like disasters, where on-time decision-making is critical for various time-sensitive applications, the incapability of evacuation teams and monitoring frameworks to monitor real-time dynamics viz. health parameters and environmental information can deteriorate the on-time and orderly evacuation of the stranded persons. The power grids or source of power also get affected due to the destructive impact of the disasters and might result in the unavailability of power supply in disaster-affected areas. Hence, the majority of devices in the post-disaster phase operates primarily on battery-sourced power [25]. These devices remain alive for a limited period of time, and need to be recharged. Hence, the operations of these devices must be energy-aware to keep these devices alive for an elongated period.

1.2. Motivations

Evacuation is the key in the post-disaster management activities and attracting more and more attentions of the nations, industry and academia around the world. The on-time and orderly evacuation of stranded persons from disaster-affected areas can save lives and reduce the destructive effects of disasters on human health effectively. However, for effective disaster evacuation, the real-time situation awareness viz. damages to the paths, physical environment and monitoring of stranded persons is crucial [26] and provides a holistic picture of the disaster-affected areas to the evacuation teams.

The advancements in sensor technology and wireless communication, and their assimilation in the internet of things (IoT) [27] has promoted the wide-scale deployment of smart things and mobile devices in various domains like disaster management [28], healthcare [29], transportation [30], industrial manufacturing [31], and alike. The integration of IoT network with cloud computing has provided these smart things and mobile devices higher storage and computation capabilities, and made the system to analyze the physical world scenarios for different domains remotely. The advent of fog computing in Cloud-IoT scenario has further exploited the computation functionalities of the cyber space to provide shorter response, location-aware computation and less dependency on network bandwidth [32] [33]. The placement of fog-devices at the network edge, near to data sources, and away from cloud servers, makes this paradigm suitable for time-sensitive applications.

In situations like disasters, where entire communication infrastructure is highly affected and most of the time leads to the complete breakdown, the aggregation of data from the sensors, and relay to the cloud servers, requires a kind of ad hoc networking infrastructure. The UAVs facilitates various such data-related activities in the disasters by acting as mobile relay [34]. UAVs can reach in such hostile situations, and operate as relay nodes in facilitating the communication of ground nodes with the remote data centers [35] [36] [37]. The integration of these technological paradigms, and addressing of evacuation-related challenges can end up in an effective on-time and orderly evacuation system.

1.3. Focus

In the times where the quality of life is quantified in terms of up to what extent a human can achieve the sustainability regarding health, living, handling of unexpected events and other matters, the technology plays an essential role in every aspect of human life. The incorporation of ICT in the domain of disaster management is one such dimension, which focuses on the sustainability of human beings regarding the handling of unexpected disaster events [38]. In this paper, a cyber physical system (CPS) is proposed that takes into account various challenges of the disaster evacuation, so an effective on-time and orderly evacuation of stranded panicked persons can be realized. The CPS can be considered as the orchestration of physical systems and distributed computing, where properties of the physical systems are acquired by the transducers and analyzed by the computation resources of the cyber systems [39]. The proposed system operates in two spaces: physical and cyber. Physical space facilitates the acquisition of various disaster-related attributes, using wireless body area network (WBAN)-assisted biosensors and behavioural sensors, and IoT-assisted environmental sensors. It also provides alerts to the concerned stakeholders (stranded persons, evacuation teams and medical professionals). The cyber space houses various data-analytics layers and comprises of two subspaces: fog and cloud. The fog space employs local data analytics for time-sensitive and energy-aware computation using fog computing and relays the acquired physical data to the remote cloud servers in the cyber space. The fog space helps in
providing real-time panic-health diagnostic and alert services, and enables two-factor energy efficiency of fog devices operated in disaster-affected areas using data reduction. It houses three layers: synchronization (SYN), panic wellbeing determination and smart decision making (PWD) and energy conservation layer (ECL).

After processing at fog space, the data advance to the cloud space for panic severity analysis and disaster mapping. The cloud space employs two layers, namely Panic Severity Analysis (PSA) Layer and Disaster Mapping Layer (DML). The PSA monitors and predicts the panic severity of the stranded persons using conditional probabilistic analysis and seasonal auto regression integrated moving average (SARIMA) respectively, whereas the DML employs geographical population analysis (GPA) to identify the critical regions and evacuation-priority within those regions based on the determined panic severity of the stranded persons. DML also converge the evacuation maps to the actual situations, based on the monitored disaster status of the routes. The knowledge of evacuation routes, identified critical regions and panic severity-based evacuation priority of the stranded person in those regions provides the evacuation teams with the capability to plan their strategy for on-time and orderly evacuation.

1.4. Contributions

The proposed CPS has a significant set of contributions in the domain of energy-aware disaster-oriented healthcare and evacuation as follows.

- This paper contributes a smart framework for panic-based on-time and orderly evacuation of the stranded persons.
- This paper provides a fog-assisted two-factor energy efficiency approach using data reduction.
- This paper provides a data reduction approach names as Novel Event Identification to identify two-dimensional duplicate data.
- This paper provides an approach names as Geographical Population Analysis to identify the disaster critical regions based on the panic severity of the stranded persons.

1.5. State-of-the-Art Literature and Paper Organization

Table 1 depicts various significant state-of-the-art related works. The table represents the major contributions of these state-of-the-art works, and compare them based on nine feature viz. Fog/Edge Computing (FC/EC), Cloud Computing (CC), IoT, Real Time Monitoring (RTM), Prediction Modeling (PM), Strategy Based Evacuation (SBE), Healthcare Aspect (HCA), Information Sharing (IS) and Energy Efficiency Approach (EEA). The tick (√) indicates that the work comprises of the corresponding feature, and cross (×) indicates that the work lacks the corresponding feature. The feature EEA also mentions the approaches which have been employed by the corresponding works for achieving energy efficiency. The comparison depicts that none of the evacuation-based work has considered the healthcare aspect during the process of evacuation. The literature review has also not found any smart healthcare framework regarding the panic attacks. Based on the analysis of the literature review and comparison of the state-of-the-art works, the presented CPS has focused on the criticality of panic-based healthcare during disasters, and proposed a panic-based evacuation system that enables on-time and orderly evacuation of the stranded persons and also considers the energy constraints of the devices operated in disaster-affected areas.

This paper has been organized into five parts. The second part presents the proposed CPS and discusses its various subsystems. The third part evaluates the performance of the proposed system. The fourth part discusses a case study related to the coronavirus disease 2019 (COVID-19) based panic. The fifth part concludes the findings from the presented research.

2. PROPOSED SYSTEM

The proposed CPS operates in two spaces: physical and cyber, as shown in Fig. 1. The physical space facilitates the process of data acquisition through various sensors and the cyber space houses various data analytics layers. The cyber space comprises of two subspaces, namely fog space and cloud space. Fog space employs fog computing-based local data analytics for time-sensitive and energy-aware computation at the fog nodes. It houses three layers: SYN, PWD and ECL. The acquired data from physical space are processed at fog space, and finally stored at the cloud storage in cloud space. The cloud space employs two layers namely PSA Layer and DML, and facilitates the analysis of panic severity of the stranded persons, and disaster mapping by converging evacuation maps to the actual situation, and identification of panic severity-based critical regions, and prioritizing of the evacuation of panicked persons in those regions. The proposed system facilitates on-time and orderly evacuation of the stranded persons. Each space of the proposed CPS has been explained as follows.

2.1. Physical Space

The responsibility of the physical space is to acquire the various disaster-related attributes and provide alerts to the concerned stakeholders (stranded persons, evacuation teams and medical professionals). This space collects the panic health (PanHealth)-related attributes of the stranded persons, and the disaster environment (DisEnvi)-related attributes of the surroundings, as shown in Table 2. The proposed system employs biosensors, behavioral sensors and WBAN for acquiring PanHealth attributes [18]. The PanHealth-related physiological attributes like heart rate, breathlessness, chest pain, nausea and
### TABLE 1. State-of-the-art comparison.

| Authors                      | Major contribution                                                                 | Year | FC/EC | CC  | IoT | RTM | PM  | SBE | HCA | IS  | EEA |
|------------------------------|-------------------------------------------------------------------------------------|------|-------|-----|-----|-----|-----|-----|-----|-----|-----|
| Xu et al. [6]                | Relationship-based personalized evacuation scheme                                   | 2018 | ✓     | ✓   | ✓   | ✓   | ✗   | ✓   | ✗   | ✓   | ✗   |
| Bhattacharjee et al. [40]    | Crowdsensing-based evacuation maps building using smartphone-based delay tolerant networks | 2019 | ✓     | ✗   | ✓   | ✓   | ✗   | ✓   | ✗   | ✓   | ✗   |
| Karthik and Suja [41]        | Wireless Sensor Network (WSN)-based geographic map-oriented path discovery to multiple exits | 2019 | ✗     | ✗   | ✓   | ✓   | ✓   | ✗   | ✓   | ✗   | ✓   |
| Fathy and Barnaghi [27]      | Energy-aware communication through reduced data transmission                         | 2019 | ✗     | ✗   | ✓   | ✓   | ✓   | ✗   | ✓   | ✗   | ✓   |
| Ejaz et al. [42]             | Coverage-area based UAV scheduling for energy efficient data collection              | 2020 | ✗     | ✓   | ✓   | ✗   | ✗   | ✓   | ✓   | ✓   | ✗   |
| Akmandor [43]                | Sensor-based machine learning inference and compression                              | 2018 | ✗     | ✗   | ✓   | ✓   | ✓   | ✗   | ✓   | ✓   | ✓   |
| Santamaria et al. [44]       | Cognitive Intelligence-based human activity using behavioral sensors                 | 2018 | ✓     | ✓   | ✓   | ✗   | ✗   | ✓   | ✓   | ✓   | ✓   |
| Gia et al. [45]              | Physiological, behavioral and environmental attributes-based health monitoring      | 2019 | ✓     | ✓   | ✓   | ✓   | ✓   | ✗   | ✓   | ✓   | ✓   |
| Asghari et al. [46]          | Prediction of medical conditions for providing appropriate health services.           | 2019 | ✓     | ✓   | ✓   | ✓   | ✗   | ✓   | ✓   | ✓   | ✗   |
| Proposed CPS                 | Fog-assisted energy efficient panic-based disaster evacuation                         | 2021 | ✓     | ✓   | ✓   | ✓   | ✓   | ✓   | ✓   | ✓   | ✓   |

**Section C: Computational Intelligence, Machine Learning and Data Analytics**
sweating are acquired by the wearable biosensors, whereas the PanHealth-related behavioral attributes like dizziness, chills, trembling and choking are acquired by the wearable behavioral sensors. The mobile devices of the stranded persons act as the sink nodes [47] in the WBAN, for aggregating PanHealth attributes from the biosensors and behavioral sensors, in the physical space. The WBAN also acquires the location of the persons using GPS sensor of the sink nodes. The wifi-capability of the sink nodes provides the WBAN with an extension to integrate with the IoT network to transmit the acquired PanHealth attributes to the cyber space for advanced processing [48].

The IoT-assisted environmental sensors, present in ambient, acquire DisEnvi attributes, namely visibility range, temperature of the structures and environment, water level, smoke detection, tilt in structures and obstacle in the path. These environmental sensors are implanted in the ambient viz. in-pavements, buildings, etc. These sensors transmit the location of their own placement along with acquired DisEnvi attributes in the IoT network. The UAVs act as the sink nodes in the IoT network for aggregating DisEnvi attributes from environmental sensors, in the physical space. The acquired data by mobile devices and UAVs from Physical space are transmitted into cyber space for various data analytical processing.

### 2.2. Cyber Space

The acquired data from physical space arrive in the cyber space. The cyber space houses various data analytics layers available at the different phases of the panic-based evacuation process. This space comprises of two subspaces, namely fog space and cloud space. The explanation of each subspace is as follows.

#### 2.2.1. Fog Space

Fog space employs fog computing-based local data analytics for time-sensitive and energy-aware computation at the fog nodes. It houses three layers: SYN, PWD and ECL. In this space, two types of fog nodes, User Fog Node (UFN) and Network Fog Node (NFN), operate at the different levels of the fog network, as shown in Fig. 2, and host three layers of fog space, as shown in Fig. 1. The acquired PanHealth data using WBAN sensors, from physical space, are transmitted to the persons’ mobile devices. These devices act as low-level fog nodes for PanHealth data and are called as UFNs in the fog network. The UFNs are present in the proximity of the persons and provide local data analytics for time-sensitive and energy-aware computation. The UFNs also act as smart gateways for WBAN, by housing three layers: SYN, PWD and ECL, and extend the WBAN to the IoT network.

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**FIGURE 1.** Architecture of panic-oriented evacuation-based cyber physical system.

**FIGURE 2.** Fog Network.
The acquired DisEnvi data using IoT-assisted environmental parameters, from physical space, and the locally processed PanHealth data from UFNs in fog network, are transmitted to the UFNs. These UFNs act as sinks for DisEnvi data and as upper level fog nodes for UFNs processed PanHealth data in the fog network. These devices are called as NFNs in fog space. The NFNs fly in proximity to the environmental sensors and mobile devices, for aggregating DisEnvi and PanHealth data, and providing energy-aware computation to the aggregated data by housing two layers: SYN and ECL, as shown in Fig. 1. The detailed explanation of each layer of the fog space is as follows.

### 2.2.1.1. Synchronization Layer

The synchronization layer acts as the entry point to the cyber space, for the data acquired from physical space. This layer is present at both the UFNs and NFNs and performs the task of global synchronization of the acquired data. The remotely deployed sensors have different internal clocks: non-synchronized, synchronized and no clock [49], and the acquired data from these sensors do not synchronize globally. Hence, the proposed CPS has programmed the gateway nodes, i.e., UFNs in WBAN and NFNs in IoT network for synchronizing the acquired PanHealth data and DisEnvi data, respectively. These gateways globally synchronize the acquired data using absolute global time stamps. These gateways tag the absolute global time instances on the values of the acquired attributes, which is the output the logistic regression, and synchronize the various events on the global timescale. The global synchronization of acquired data helps in depicting the holistic picture of the disaster-affected area. It facilitates various time-sensitive activities like real-time analysis of panic wellbeing, panic severity monitoring and prediction and disaster mapping. The synchronized PanHealth data transmit to the UFN-hosted PWD layer, whereas the synchronized DisEnvi Data transmit to the NFN-hosted ECL, as shown in Fig. 1.

### 2.2.1.2. Panic Wellbeing Determination and Smart Decision Making Layer

The UFNs host this layer for local data analytics and real-time panic wellbeing determination at the users’ premises. This layer, based on the acquired PanHealth data, continuously classifies the panic wellbeing (PW) of the stranded person in one of the two classes, namely Normal (NOR) or Abnormal (ANOR). The class of NOR depicts that the PW of the persons is normal, and does not require any special consideration in the process of evacuation for the current instance. The class of ANOR depicts that the PW of the person is abnormal, means the person is panicked, and requires immediate medical guidance, and prioritized consideration further in the process of evacuation analytics. The PanHealth data of the stranded persons at a particular instance $t_i$, in the proposed system, comprise of nine acquired attributes and forms a PanHealth vector ($PaHi_i$). The incidence of a panic attack is determined in that $PaHi_i$, based on the identification of any four and more symptoms. Hence, the PWD layer employs logistic regression [50] for classifying the PW of the stranded persons. The logistic regression fits for the categorical classifications, where decision boundaries are defined based on the threshold of various scenarios, and the same is required in the determination of PW of the stranded persons. The logistic regression defines the decision boundaries as linear or nonlinear and classifies the data into categorical classes. The logistic regression uses Eq. 1 to classify the PanHealth records based on the threshold using a function, as follows.

$$\gamma = \frac{e^{\omega_0 + \omega_1 PaHi_i}}{1 + e^{\omega_0 + \omega_1 PaHi_i}}$$

where $\gamma$ is the output the logistic regression, $e$ is the base of natural logarithmic, $\omega_0$ is the intercept of bias, $\omega_1$ is the coefficient of the PanHealth record and $PaHi_i$ is the PanHealth record of the person at the time instance $t_i$.

| S. No. | Dataset     | Description                                                                 | IoT technology                                                                 | Attributes                                                                 |
|-------|-------------|------------------------------------------------------------------------------|------------------------------------------------------------------------------|----------------------------------------------------------------------------|
| 1.    | PanHealth dataset | Data about the health related physiological and behavioral attributes of the stranded persons. | Optical Heart Rate Sensors, ECG Sensors, Contraction Sensors, Capacitive Humidity Sensors, Inertial Sensors, Accelerometer, Piezoelectric Sensors, GPS Sensors. | Heart rate, Breathlessness, Chest pain, Nausea, Sweating, Dizziness, Chills, Trembling, Choking, Location. |
| 2.    | DisEnvi dataset | Environmental data regarding the surroundings of the stranded persons.     | Infrared Sensors, Temperature Sensors, Ultrasonic Depth Sensors, Photoelectric Sensors, Electrolytic Sensors, GPS Sensors. | Visibility, Temperature, Water level, Smoke detection, Tilt in structures, Obstacle range, Disaster Location. |

The acquired DisEnvi data using IoT-assisted environmental sensors, from physical space, and the locally processed PanHealth data at UFNs in fog network, are transmitted to the UAVs. These UAVs act as sinks for DisEnvi data and as upper level fog nodes for UFNs processed PanHealth data in the fog network. These devices are called as NFNs in fog space. The NFNs fly in proximity to the environmental sensors and mobile devices, for aggregating DisEnvi and PanHealth data, and providing energy-aware computation to the aggregated data by housing two layers: SYN and ECL, as shown in Fig. 1. The detailed explanation of each layer of the fog space is as follows.
The categorical classification requires the output of the response to be either 1 or 0, and the Bernoulli distribution considers the probability of $PW = 1$ (ANOR), if the output of the function is $\gamma$, and correspondingly the probability of $PW = 0$ (NOR) if the output of the function is $\gamma - 1$. But the linear relation of $\gamma$ and $PaH_i$ violates the constraint of the probability to range between 0 and 1. Hence, the logistic regression uses sigmoid function, which provides s-shaped curve to classify the data into one of the category using the threshold of the output of the function, as shown in Eq. 2.

$$PW = \text{sig}(\gamma) = \frac{1}{1 + e^{-\gamma}}$$  \hspace{1cm} (2)

where $PW$ depicts the class of the determined panic wellbeing, and $\text{sig}(\gamma)$ is the categorized value of the logistic regression output $\gamma$.

The fog-based local data analytics functionality at the UFN enables real-time PW determination and alert generation to concerned stakeholders. The alert generation provides on-time diagnostic alerts and medical guidance in the event of a panic attack, to the person and his/her relatives for immediate care, diagnostic alerts and medical guidance in the event of a panic concerned stakeholders. The alert generation provides on-time energy-consumption consideration is critical for the effective operation of evacuation in disaster-hit areas, where the source of power regeneration is not available [27]. Hence, the energy-aware computation at the UFNs and NFNs can extend the lifetime of fog nodes and guarantee the quality of service.

In IoT networks, the data reception and transmission (DRecTrans) poses as the dominant factor for the energy consumption of the devices, and consumes higher energy than the data processing [50] [51]. However, by limiting the communication between the devices, the DRecTrans energy consumption of the devices can be reduced [52], and compensated for extending the period for other functionalities. The ECL of the proposed system considers these factors, responsible for energy consumption in fog nodes, and enables energy-efficient operations of the devices through energy-aware computation using data reduction at the fog nodes. The ECL focuses on three dimensions for energy-aware computation: data reduction, data quality and energy conservation. The ECL addresses concerns by reducing data transmission from UFNs to NFN and from NFN to cloud servers in such a manner that the quality of data can be retained by reconstructing the same data as if they were from the source, and the energy can be conserved through reduced DRecTrans operations. The ECL employs the following energy model to determine the energy consumption of UFNs and NFNs.

**Algorithm 1 Panic well-being determination and alert generation**

**Input:** PanHealth Record $PaH_i$, time instance $t_i$

1: Until the person get evacuated
2: Determine the current time stamp $t_i$
3: Map the $PaH_i$ to the feature space
4: Determine the PW of the mapped sample using, $\gamma = \frac{e^{\xi_{ANOR} PaH_i}}{1 + e^{\xi_{ANOR} PaH_i}}$
5: $PW = \text{sig}(\gamma) = \frac{1}{1 + e^{-\gamma}}$
6: Send Diagnostic alert (PW) to the person
7: IF $PW == \text{ANOR}$, then
8: Send Guidance alert to person & relatives
9: Transfer ($PaH_i \cup PW$) to the ECL
10: Transfer ($PaH_i \cup PW$) to the ECL
11: Exit

**Output:** PW of the stranded person and generated alerts

2.2.1.3. **Energy Conservation Layer**

During disasters, the infrastructure and essential services are highly affected by the destructive nature of the disasters, and most of the time leads to the complete breakdown. In such hostile situations, the majority of disaster management operations primarily operate on battery-powered devices. These devices remain alive for a limited period of time, and need to be recharged. In the proposed system, the fog devices UFNs and NFNs operate in the disaster-affected areas. Therefore, the inefficient energy consumption in these devices could have a negative impact on the power-constrained fog operations in hostile situations like disasters. Since, the fog devices in the proposed system facilitate data collection, time-sensitive local data analytics, data caching and transmission relay, their energy-consumption consideration is critical for the effective operation of evacuation in disaster-hit areas, where the source of power regeneration is not available [27]. Hence, the energy-aware computation at the UFNs and NFNs can extend the lifetime of fog nodes and guarantee the quality of service.
\[ E_{P_{-UFN}} = m \times \beta \text{ Joules} \] (4)

\[ E_{T_{-UFN}} = m' \times \eta \text{ Joules} \] (5)

Based on Equations 3–5, the total energy consumption of a UFN \((E_{UFN})\) for relaying acquired data from sensors to NFN, for a particular time instance is shown in Eq. 6. The ECL at the UFN works on optimizing the \(E_{UFN}\) by employing a module named Novel Event Identification (NEI), which reduces the acquired data from sensors, so the transmission energy consumption \(E_{T_{-UFN}}\) can be minimized and resultantly could optimize the overall \(E_{UFN}\).

\[ E_{UFN} = (m \times \alpha) + (m \times \beta) + (m' \times \eta) \text{ Joules} \] (6)

The energy model further considers the data received from UFNs and environmental sensors, to NFN, in the form of packets, which may have variable length. The proposed energy model only considers the number of data values, from a source (UFN or environmental sensor) as the length of the packet. During the relaying of data to the NFN, the model considers \(n\) number of UFNs and environmental sensors, which transmit the data in an instance to that NFN. For collecting each packet, the energy consumption at the NFN depends upon the size of the packet. Let say a packet is of variable length \(h\). Then, the energy consumption \((\Psi)\) for collecting each packet is directly proportion to the length of packet as shown in Equations 7 and 8, and the total energy consumption \((E_{R_{-NFN}})\) for collecting \(n\) data packets at NFN is shown in Eq. 9.

\[ \Psi \longrightarrow h \] (7)

\[ \Psi = \rho \times h \text{ Joules} \] (8)

where \(\rho\) is the constant, which accounts for the increasing energy consumption with increase in packet length and vice-versa.

\[ E_{R_{-NFN}} = \int_{i=1}^{n} \Psi_i \text{ Joules} \] (9)

The model considers the energy consumption of an NFN for locally caching, and processing a single packet as \(\tau\) Joules. The total energy consumption \((E_{P_{-NFN}})\) for locally caching and processing the received and filled \(n'\) data packets at NFN is shown in Eq. 10.

\[ E_{P_{-NFN}} = n' \times \tau \text{ Joules} \] (10)

The model considers the energy consumption of an NFN for transmitting a single packet as \(\Psi'\) Joules, which depends upon the length of the packet \(h'\), is shown in Equations 11 and 12.

\[ \Psi' \longrightarrow h' \] (11)

\[ \Psi' = \rho \times h' \text{ Joules} \] (12)

Then, the total energy consumption \((E_{T_{-NFN}})\) of an NFN for transmitting \(n'\) data packets is shown in Eq. 13.

\[ E_{T_{-NFN}} = \int_{i=1}^{n'} \Psi'_i \text{ Joules} \] (13)

Based on Equations 9–13, the total energy consumption \((E_{NFN})\) of an NFN for relaying aggregated data from UFNs and environmental sensors, to the cloud server for a particular time instance is shown in Eq. 14.

\[ E_{NFN} = E_{R_{-NFN}} + E_{P_{-NFN}} + E_{T_{-NFN}} \text{ Joules} \] (14)

The ECL at the NFN works on optimizing the \(E_{NFN}\) by employing a module named Dimensionality Reduction, which reduces the features of aggregated data, so the transmission energy consumption \((E_{T_{-NFN}})\) can be minimized. Even the energy consumption during the data collection \((E_{R_{-NFN}})\) at NFN is also optimized due to the energy-aware computation of data by NEI. Hence, the entire resultant of NEI and Dimensionality reduction helps in minimizing the \(E_{NFN}\). Each module of this layer on UFNs and NFN is explained as follows.

2.2.1.3.1. Novel Event Identification

The ECL employs a module named Novel Event Identification (NEI) at UFNs to avoid consecutive duplicate PanHealth data transmission to the NFN. The WBAN in physical space continually acquires the PanHealth events, and UFNs in fog space continually monitor the panic wellbeing. However, the PanHealth attributes may not change or remain the same, depend upon the body and surrounding events of the stranded person. In such a scenario, the transmission of data to the NFN may involve the consecutive duplicate events, and even consecutive duplicate attribute values too. This can result in energy consumption for transmitting the duplicate data. The energy of the UFNs can be conserved by avoiding such duplicate data transmissions to the NFN. Hence, the NEI focuses on the identification of duplicate data, i.e. consecutive duplicate events and consecutive duplicate attribute values, and allows only novel events and novel attribute values to relay further in the fog space.

The sink node of the WBAN arranges the PanHealth attributes acquired at the time instance \(t_i\), in a well-defined sequence to form a PanHealth vector \((PaH_i)\), and follows the same sequence throughout the process. The PWD layer classifies the PanHealth event \(PaH_i\) at \(t_i\) into one of the \(PW\) class and appends the classified \(PW\) value to the \(PaH_i\). This \(PaH_i\) is analyzed by the NEI to identify the novel PanHealth events, and attribute values. The NEI creates a checkpoint in the time-space, when a novel event is encountered, stores it in the log memory of the UFN, and transmits the event to the NFN.
The NEI determines the duplication of the subsequent events one by one, by determining the fully matched event, fully unique event and partially matched event, using a piecewise match function as shown in Eq. 15.

If the match function determines that the subsequent event, i.e. \( PaH_{i+1} \) is fully matched, the NEI does not transmit the subsequent event and continues to determine the matching between the unique event and next subsequent events. The UFN uses cache memory to store the most recent event. If NEI determines any subsequent event fully unique, it creates a new checkpoint to the time instances of the newly identified novel event, and saves the newly identified novel event in the log memory, and transmits that event to the NFN. If the NEI determines that the subsequent event partially matches with the unique event, NEI constructs a binary sequence of the partially matched subsequent event using function \( \text{constructBinSeq} \) that employs AND operation to determine the attribute values of the partially matched event, which are different from the unique event, and saves the binary sequence in \( \text{binSeq} \). Based on the \( \text{binSeq} \) value, the function \( \text{omitFeatures} \) omits the matching values of the partially matched event and makes the compressed form of the partially matched event, i.e. \( PaH_{\text{Comp}} \). The NEI appends the corresponding \( \text{binSeq} \) with the compressed record (\( PaH_{\text{Comp}} \)) and sends it to the NFN. In this manner, the NEI also avoids the subsequent duplicate attribute values of the PanHealth data. The entire working of NEI is shown in Algorithm 2. Here, in Algorithm 2, \( uRec \) and \( mRec \) signify the unique PanHealth record and subsequent matching PanHealth record (which is matching with the unique record), respectively.

\[
\text{match}(PaH_{i}, PaH_{i+1}) = \begin{cases} 
\emptyset & (PaH_{i} \cap PaH_{i+1}) = PaH_{i} = PaH_{i+1} \\
PaH_{i+1} & (PaH_{i} \cap PaH_{i+1}) = \emptyset \\
PaH_{i} - (PaH_{i} \cap PaH_{i+1}) & (PaH_{i} \cap PaH_{i+1}) \subset PaH_{i} \\
+\text{binSeq} & (PaH_{i} \cap PaH_{i+1}) \subset PaH_{i} 
\end{cases}
\]

The function in Eq. 15 matches the subsequent PanHealth event \( PaH_{i+1} \) with the saved unique event \( PaH_{i} \), and only transmits the outcome of the function based on three different criteria for fully matched, fully unique and partially matched event, respectively. The outcome of the match function determines the value of \( m' \) (refer Eq. 5), such that \( m' \leq m \). In this manner, the transmission energy consumption of the UFN (\( E_{UFN} \)) minimizes and resultanty, the overall energy consumption of the UFN (\( E_{UFN} \)) optimizes, by reducing the data transmission from UFN to NFN.

**Algorithm 2 Novel Event Identification**

**Input:** Temporal PanHealth events

1. Set Time counter \( i \) as 0
2. Set \( \text{binSeq[|]} \) as \( \emptyset \)
3. For every temporal PanHealth event \( PaH_{i} \),

   4. Create a checkpoint at \( t_i \)
   5. Flush log memory of UFN
   6. \( uRec = PaH_{i} \)
   7. Save \( uRec \) in log
   8. If \( \text{isempty(binSeq[t_i])} == 0 \), then
   9. \( \text{PaHComp} = \text{omitFeatures(PaH}_{i}, \text{binSeq[t_i]} \) \)
   10. \( \text{PaHComp} = \text{PaHComp} \cup \text{binSeq[t_i]} \)
   11. Send \( \text{PaHComp} \) to NFN
   12. Else (Send \( PaH_{i} \) to NFN)
   13. \( mRec = PaH_{i+1} \)
   14. Save \( mRec \) in log
   15. If \( \text{match(uRec,mRec)} == uRec == mRec \), then
   16. \( i++ \)
   17. Goto Step 13
   18. ElseIf \( \text{match(uRec,mRec)} == \emptyset \), then
   19. \( i++ \)
   20. Goto Step 4
   21. Else
   22. \( i++ \)
   23. \( \text{binSeq[t_i]} = \text{constructBinSeq(uRec,mRec)} \)
   24. Goto Step 4
   25. Exit

**Output:** Novel Data Transmission

### 2.2.1.3.2. Dimensionality Reduction

The NFN acts as the ultimate sink for data from various sources viz. UFNs and environmental sensors. The data arrived at the NFN includes the temporal PanHealth and DisEnvi events of the various stranded persons and various locations, respectively, which make the acquired data at the NFN a high dimensional data. The high dimensional data present various challenges like intense computation requirements, and increased error rate during analysis [55]. The transmission of such high-dimensional big data requires significant energy consumption at the NFN. The ECL employs Dimensionality Reduction (DR) module at the NFN, which addresses the issue of energy conservation at the NFN, by employing energy-aware computation using data summarization. However, the NEI-processed data from the UFN have omitted consecutive duplicate events and values, and the DR module requires the entire data for identifying the data patterns, and trends for data summarization. That is why the DR has a filler component (FL), which analyzes the collected data against the time-series to fill the missing values in the received data. It replicates the preceding value of the attributes in the missing value position, in the time series.

The DR module uses Principal Component Analysis (PCA) [56], which transforms the high-dimensional data, say \( Q_{n\times d} \) having \( n \) records and \( d \) dimensions into low dimensional subspace, say \( Q'_{p\times d'} \) having \( n \) records and \( d' \) dimensions such that \( d' < d \). PCA transforms the data in such a way that the data can be represented maximally using few dimensions. The PCA identifies those dimensions or principal components
(PC), which can retain maximum information of the common structure that exists in a dataset by using the concept of co-variance and Eigen’s (values and corresponding vectors), as shown in Equations 16 and 17. The transformation of data using Eigen vectors identify the PCs. The identified PCs or Eigen vectors depict the direction in which maximum variance of the data is retained, using Eigen values, as shown in Eq. 18. The identified PCs provide the loading factors of each dimension to project the data values on those PCs, as shown in Eq. 19. The PCs depict the maximum variance or spread of the data and are mutually uncorrelated.

\[ S = Q^T Q \]  
\[ \text{where, } S \text{ is the co-variance matrix, and } Q^T \text{ is the transpose of the column standardized dataset } Q_{n \times d}. \]

The column standardization of the dataset helps in moving the data points to the origin along with retaining the original spread of data, and the co-variance matrix analyzes the co-dependence between the dimensions.

\[ \lambda_i, v_i = S, v_i \]  
\[ \text{where, } \lambda_i \ni i:1 \rightarrow d \text{ are Eigen values for of the d-dimensions of the co-variance matrix, and } v_i \ni i:1 \rightarrow d \text{ are the corresponding Eigen vectors, such that } \lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \ldots \lambda_d. \]  
\[ \lambda_i, v_i \text{ are determined by satisfying Eq. 17. } \lambda_i \text{ show the variance of the data retained by the corresponding Eigen vectors } v_i. \]

The PCA analyzes the variance or spread of data on a direction \( v_i \) using corresponding Eigen values as shown in Eq. 18.

\[ \text{variance}(\lambda_i) = \sum_{i=1}^{d} \frac{\lambda_i}{\lambda_i} \]  
\[ \text{Algorithm 3 Dimensionality Reduction} \]

| Input | High dimensional dataset \( Q_{n \times d} \) |
|-------|-----------------------------------------------|
| 1: Column standardization of dataset \( Q \) |
| 2: Determine the co-variance matrix \( S \) of column standardized dataset \( Q \) |
| 3: Determine the Eigen values and corresponding Eigen vectors of \( S \) using, |
| 4: \( \lambda_i, v_i = S, v_i \), where, \( i :1 \rightarrow d \) |
| 5: Choose PCs account for maximum variance using cumulative variance |
| 6: Compute \( x_{ij} \) of the PC using loading factors as, |
| 7: \( x_{ij} = x_{ij}^T \times PC_j \) |
| 8: Exit |

**Output**: Reduced Dimensional dataset \( Q'_{n \times d'} \)

The employed NEI reduces the packet length \( (m') \), such that \( m' \leq m \), of the transmitting packet from the UFN; as a result, the energy consumption for collecting packets from UFNs reduces at NFN and subsequently optimizes \( E_{R_{NFN}} \). On the other side, employed dimensionality reduction at the NFN reduces dimensions of data from \( d \) to \( d' \), and results in reducing the energy consumption for transmitting a single packet \( (\Psi') \), as the length of packet reduces, and subsequently optimizes \( E_{T_{NFN}} \). In this manner, the overall energy consumption of the NFN reduces with the deployment of NEI at UFNs and dimensionality reduction at the NFN.

2.2.2. Cloud Space

The acquired data from physical space are processed at fog space, and finally stored at the cloud storage in the form of time-series data. The time series data consist of successive observations made over the time interval \([57\, [58]]\). The cloud space employs two layers, namely PSA Layer and DML. Each layer has been explained as follows.

2.2.2.1. Panic Severity Analysis Layer

Panic Severity Analysis (PSA) layer analyzes the time-series PanHealth-DisEnvi data of the panicked persons, for monitoring and predicting their panic severity in the form of Panic Severity Index (PSI). The PSI provides a probabilistic measure for analyzing the effects of the occurrence of the PanHealth- and DisEnvi-related adverse events on the panic health of the stranded persons and helps in facilitating the on-time and orderly evacuation of stranded persons. A higher value of PSI indicates the possibility of severe panic attacks. Hence, the PSI is monitored and predicted for identifying the critical regions, and evacuation priority of people in those regions. The PSI is monitored in the form of conditional probability, as shown in Eq. 21.

\[ PSI = P \left( \frac{PW}{e_1 \cup e_2 \cup e_3 \cup \ldots e_i} \right) \]  
\[ \text{Algorithm 3 Dimensionality Reduction} \]
Here, $PW$ denotes the panic health class of the stranded person, and $e_i$ denotes the occurrence of an adverse event in a particular time instance. The PSI helps the cloud servers in monitoring the panic health severity of the stranded persons. Based on the current and past monitored PSI, the PSA layer further employs SARIMA prediction model for predicting the PSI. SARIMA is the extension to the prediction model ARIMA, and considers the seasonal characteristics of the data using hyper-parameters for accounting the seasonality of the data series. The hyper-parameters in the SARIMA are similar to the parameters of the ARIMA; however, the hyper-parameters involve seasonal lag (i.e. minutes, hourly, daily, weekly, monthly, yearly), which is specified by the seasonality period variable. ARIMA employs auto regression (AR) and moving average (MA) to predict the value in a time-series based on the linear combination of present and past values, and prediction errors, respectively. ARIMA($p$, $d$, $a$) is used to predict a value in time-series, as shown in Eq. 22.

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + Z_t + \theta_1 Z_{t-1} + \cdots + \theta_a Z_{t-a}$$

where $Y_t$ denotes the stationary data value at $t^{th}$ instance, for the non-stationary data value $S_t$, using the differencing process of order $d$, such that $Y_t = S_t - S_{t-d}$. $S_t$ denotes the predicted PSI of a person. $p$ and $a$ denote the number of AR terms and MA terms, respectively. $\phi$ and $\theta$ are the AR and MA coefficients, respectively. $Y_t$ denotes the predicted value, and $Y_{t-1} \ldots Y_{t-p}$ denotes the previous $p$ predicted data values. $Z_t$ denotes random error for predicted data value and $Z_{t-1} \ldots Z_{t-a}$ denote the previous $a$ prediction errors. The Eq. 22 can be represented using lag operator ($L$) as shown in Eq. 23.

$$\phi_p(L)Y_t = \theta_a(L)Z_t$$

where

$$\phi_p(L)Y_t = (1 - \phi_1 L - \phi_2 L^2 - \phi_3 L^3 \ldots \phi_p L^p)Y_t$$

$$L^p Y_t = Y_{t-p}$$

$$\theta_a(L)Z_t = (1 - \theta_1 L - \theta_2 L^2 - \theta_3 L^3 \ldots \theta_a L^a)Z_t$$

$$L^a Z_t = Z_{t-a}$$

The SARIMA predicts the PSI based on the past values of the PSI and past predicted errors. Since the PSI is based on the number of symptoms appeared, and the duration of the panic attacks, it is significant to consider the periodicity or seasonality of the time series in ARIMA prediction. Hence, the PSA layer employs SARIMA($p,d,a$)($P,D,A$)[$V$] to predict the PSI of a stranded panicked person, as shown in Eq. 24.

$$\phi_p(L)\Phi_p(L^V)(1 - L)^d(1 - L^V)^D S_t = \theta_a(L)\Theta_A(L^V)Z_t$$

where $\Phi$ and $\Theta$ are seasonal AR and seasonal MA coefficients, respectively. $p$ is the order of nonseasonal AR terms, $d$ is the order of nonseasonal differencing, $a$ is the order of nonseasonal MA terms, $P$ is the order of seasonal AR (SAR) terms, $D$ is the order of differencing or power of $(1 - L^V)$, $A$ is the order of seasonal MA (SMA) terms and $V$ is the seasonality period.

The terms $\Phi_p(L^V)$ and $\Theta_p(L^V)$ converge the entire seasonal prediction function as shown in Equations 25 and 26.

$$\Phi_p(L^V) = 1 - \Phi_1 L^V - \Phi_2 L^{2V} - \Phi_3 L^{3V} - \cdots - \Phi_p L^{pV}$$

$$\Theta_A(L^V) = 1 - \Theta_1 L^V - \Theta_2 L^{2V} - \Theta_3 L^{3V} - \cdots - \Theta_A L^{AV}$$

The PSI prediction using SARIMA involves four phases [59]: (I) Model Identification, (II) Parameter Identification, (III) Diagnostic Checking and (IV) Prediction. In model identification phase, the time plot of the data is inspected for stationary data and determines the value of $d$, so the variance of data can be stabilized. After the identification of $d$, the preliminary values, i.e. $p$, $a$, $P$, $D$ and $A$ are identified in this phase using Partial Autocorrelation Function (PACF) and Autocorrelation Function (ACF).

The PACF determines the required order of AR terms i.e. $p$, whereas the ACF depicts the amount of linear dependence between data values of time series, which are separated by a lag of $a$. In parameter identification phase, the parameter and corresponding standard errors are estimated using statistical measures: lease square estimation (LSE), maximum likelihood (ML) and Yule–Walker. In diagnostic checking, different models are evaluated, and their residuals are analyzed. The model, which has the least residual or values of Mean absolute Error (MAE), Mean square error (MSE) and Root mean square error (RMSE), fits well and is selected. In prediction phase, the model predicts the PSI based on the fitted model. The PSI prediction using SARIMA is illustrated in Algorithm 4. The monitored and predicted PSI of the stranded persons are transmitted to the DML, which analyzes the PSI time-series to ascertain the highest panic severity of the person for a particular future time-frame (ranges from current instance to a particular future instance), so panicked critical regions and evacuation priority of the stranded persons in those regions could be identified.

**Algorithm 4 Panic Severity Index Prediction**

**Input:** Monitored PSI Time-series data

1. Determine the differencing values for stabilizing the data.
2. Examine PACF, and ACF Plots to decide the structure of SARIMA
3. Determine the AR and MA coefficient for both non-seasonal and seasonal
TABLE 3. GPA-based PSI classification.

| S. No. | Class                  | PSI Value                        | Person Node Color | PrioW |
|-------|------------------------|----------------------------------|-------------------|-------|
| 1.    | Intense Panic Severity | $\geq 0.88$                      | Black             | 4     |
| 2.    | Mild Panic Severity    | $0.6 \leq \text{PSI} < 0.88$    | Red               | 3     |
| 3.    | Low Panic Severity     | $0.32 \leq \text{PSI} < 0.6$    | Sky Blue          | 2     |
| 4.    | Non-Panicked           | $\text{PSI} < 0.32$             | Green             | 1     |

4: Select the model with optimized error i.e. minimum MSE, MAE, and RMSE values.
5: Predict the PSI at $t^{th}$ time instance using the selected model
6: Exit
Output: Predicted PSI

2.2.2.2. Disaster Mapping Layer
The holistic picture of the disaster-affected area is very critical for effective evacuation operations. However, the conditions change very quickly because of the dynamic nature of the disasters viz. flooding in the streets, smoke on the paths, debris, etc. In such kind of scenarios, the convergence of evacuation maps to the actual situation, identification of critical regions and prioritizing of the evacuation of panicked persons in those regions can facilitate the on-time and orderly evacuation of the stranded persons. Therefore, the DML of the cyber space analyzes the DisEnvi-related information for converging the disaster evacuation maps to the actual situation of the area, and PSI time-series data for identifying the critical regions and prioritizing the evacuation of stranded persons in those regions. The DML analyzes the DisEnvi attributes and compares those with their threshold for determining the status of location, i.e. passable or impassable. DML based on the determined status of the location pinpoints the disaster status on the mapped location in the evacuation map. The DML also analyzes the PSI time-series for ascertaining the highest panic severity of the persons in a particular future time-frame (ranges from current instance to a particular future instance), so panic-based critical regions and evacuation priorities of the stranded persons in those regions could be identified. The DML proposes Geographical Population Analysis (GPA) for identifying the critical regions based on the determined highest PSI of the persons. The GPA classifies the population of people, based on their determined highest PSI into four classes, along with their evacuation priority weight ($PrioW$), as shown in Table 3.

The GPA divides the entire disaster-affected area into hexagonal regions and identifies the panic-based criticality of the regions by analyzing the population of the different PSI classified persons in that region, and correspondingly identifies the region priority ($RegPrio$), as shown in Table 4, and Eq. 27, respectively. The entire working of the DML layer is illustrated in Algorithm 5.

\[
RegPrio = \int_{c=1}^{4} PrioW_c * pShare_c
\]

where $PrioW_c$ defines the evacuation priority weight associated with the particular class $c$ population, and $pShare_c$ depicts the population share of a particular class $c$ in a region.

The knowledge of evacuation routes, identified critical regions and panic severity-based evacuation priority of the stranded person in those regions provides the evacuation teams with the capability to plan their strategy for on-time and orderly evacuation.

Algorithm 5 Disaster Mapping

Input: PSI time-series data, DisEnvi temporal data, current instance $t_i$, and Future range $r$

1: For every time instance $t_i$,
2: For every deployed DisEnvi sensor $s_j$,
3: If disasterStatus > threshold, then
4: If location($s_j$) is highlighted, then
5: Goto Step 2
6: Else highlight($s_j$)
7: Else
8: If location($s_j$) is highlighted, then
9: unhighlight($s_j$)
10: Else Goto Step 2
11: For every location of the stranded persons loc$k$,
12: Pinpoints the location of the person with node
13: Determine highest PSI in a future using,
14: $PSI_k = \text{highestPSI}(t_i, t_i + r)$
15: Color the Node using, Table 3
16: Set Evacuation priority using,
17: $EvacPrior_k = PSI_k$
18: For every $i^{th}$ region of the disaster-affected area,
19: Determine population of different colored nodes
20: Color the region using, Table 4
21: Determine the RegPrio using,
22: $RegPrio = \int_{c=1}^{r} PrioW_c * pShare_c$
23: Exit

Output: Disaster Evacuation Map and Critical Regions
3. PERFORMANCE EVALUATION

This section has evaluated the performance of the proposed CPS through various experiments. It consists of five parts: data collection, panic wellbeing and smart decision evaluation, fog-based energy efficiency evaluation, cloud-based panic severity prediction evaluation and disaster mapping efficiency. Each part has been explained as follows.

3.1. Data Collection

The research in the domain of panic-oriented disaster evacuation is one of its kind, and there was not available any panic symptom-based dataset on any online repository. Hence, the data have been prepared by referring dataset [60], and in consultation with a medical professional Dr. Arvind Manchanda. He is M.D. in Medicine and Medical officer with Punjab Health Department (India). The PanHealth dataset of 8000 persons has been created, and their PW has been determined based on the onset of at least four out of nine symptoms. For DisEnvi dataset, a simulation of 61 deployed sensors in a particular location of Kochi City in the province of Kerala (India) has been created using CupCarbon [61]. The sensors have been assumed to sense the water level of the streets and show the status of flooding based on the programming of the sensors. The programmed sensors have given the random values of disaster status, to simulate the random real-world scenario of a flooded area. The PanHealth records have been mapped to the various locations of that specified area of the city, to simulate the scenario, where persons have been stranded in a flood-affected area.

3.2. Panic Wellbeing and Smart Decision Evaluation

The PWD layer locally determines the PW of the stranded persons at their mobile devices in the closest proximity. This layer employs logistic regression (LR) for classifying PW as NOR or ANOR. The current evaluation has used statistical analyses viz. accuracy (correct classification rate), sensitivity (true positive rate), specificity (true negative rate) and F-Measure for comparing the classification performance of LR with state-of-the-art classification approaches namely J48 Decision Tree (J48), Naïve Bayer (NB) and k-Means Clustering (KMC). The evaluation methodology has considered a dataset with 8000 records for 10-fold cross-validation in R-studio [62]. The evaluation has used glm function of R-language for LR, Rweka package for J48, e1071 package for NB and kmeans function of R-language for KMC in R-Studio. During the entire evaluation, only the classification approach has been changed, and the rest parameters kept same. The performance of the employed and comparing approaches has been shown in Fig. 3 (a). The outcomes of employed classification approaches has depicted that the accuracy of the LR is highest (99.88%) as compared to the J48, NB and KMC, having 98.79, 97.46 and 65.96%, respectively. The sensitivity achieved by LR is 99.98%, and it is also the highest of all. Similarly, the performance of LR has further depicted that the achieved specificity and F-measure are higher as compared to the other approaches with 99.77 and 99.88%, respectively. The overall observation of the performance analysis has depicted that LR is much more effective in classifying the PW of the stranded persons and outperforming the other employed classification approaches.

The PWD evaluation has further acknowledged the efficiency of LR by analyzing the classification time, as shown in Fig. 3 (b). The results have depicted that the LR consumes lesser time in classifying the PW of the stranded persons as compared to the other employed classification approaches. The analysis has also acknowledged the capability of LR in classifying the data in a shorter time, irrelevant of the size of data. The overall inference of the results depicted in Fig. 3 (b) has clearly represented the capability of LR in generating real-time alerts to the concerned stakeholders at the Fog layer.

3.3. Fog-based Energy Efficiency Evaluation

The proposed ECL caters for energy-efficiency in the IoT network using energy-aware computation at the relays (UFNs and NFNs) through data reduction during the transmission of data from sensors to remote cloud servers. The ECL has employed NEI at the UFNs to avoid the transmission of consecutive duplicate data traffic to the NFN. A c Program has been developed based on the Algorithm 2 for implementing the functionality of NEI. Fig. 4 (a) shows the comparative analysis of the same set of data for transmission from a UFN employing NEI and a UFN having no NEI. The analysis has depicted that NEI enables 38.65% lesser data transmission for the time window of 100 instances, from a UFN to the NFN.

| S. No. | Region            | Population Percentage in a Region | Region Color |
|-------|-------------------|-----------------------------------|--------------|
| 1.    | Highly Panicked Region | n(B-node) ≥ 20                    | Red          |
| 2.    | Mild Panicked     | n(R-node) ≥ 30 AND n(B-node) < 20 AND n(SB-node) ≤ 50 | Orange       |
| 3.    | Low Panicked      | n(SB-node) ≥ 50 AND n(R-node) < 30 AND n(B-node) < 20 | Yellow       |
| 4.    | No panicked       | n(G-node) = 100%                  | Green        |
| 5.    | Empty             | No population                     | No Color     |
For energy consumption, the proposed energy model has assumed that all UFNs have identical energy requirements for transmission of data. The evaluation has taken into account the energy consumption characteristics of Xiaomi Redmi Note 5 pro with Android 8.1, as the energy consumption characteristics of a UFN. The energy consumption of UFN has been analyzed using Qualcomm’s Trepn Profiler [63]. The tool has analyzed that the energy consumption for receiving 1-bit data on the network is 0.22 μ Joules, and the energy consumption for transmitting 1-bit data is 0.20 μ Joules, at the speed of 750KBps. Based on the data reduction by NEI at a UFN, the proposed energy model has numerically calculated the energy consumption for each PanHealth record by considering the size of each value in a record equal to 1-bit, and subsequently the energy consumption accordingly, for transmitting the records, as shown in Fig. 4 (b). The results have compared the transmission energy consumption for a particular time window at a UFN with NEI and without NEI. The results have depicted that the average energy consumption for transmitting a single PanHealth record with NEI takes 1.227 μ Joules as compared to the average energy consumption of transmitting a single PanHealth record without NEI that takes 2 μ Joules. The results have acknowledged the energy efficiency of UFN by hosting NEI-based ECL.

The main responsibility of the NFNs is to aggregate data from environmental sensors and UFNs of a particular area, and relay to cloud. The hosted ECL on NFN provides energy-aware computation using data summarization through PCA. The PCA reduces the dimensionality of the aggregated data at the NFN. In the current evaluation, the dimensionality of the aggregated PanHealth-DisEnvi data has been reduced by implementing PCA using `prcomp` function of R-language in R-Studio. The PCA has determined ten PCs, along with their Eigen values and cumulative variance, as shown in Fig. 5 (a). The results have depicted that the first six PCs cumulatively represents >90% variance in data. Hence, the NFN has selected first six PCs and generated dataset along with these PCs (using Eq. 19), and transmitted further the summarized data along with the
FIGURE 5. (a) Principal Component Analysis of the PanHealth-DisEnvi data, and (b) DRecTrans Energy Consumption Analysis at NFN.

TABLE 5. Principal Component Analysis.

| PC  | Standard Deviation | Proportion Variance | Cumulative Variance |
|-----|--------------------|---------------------|---------------------|
| PC1 | 1.157235           | 0.2957              | 0.2957              |
| PC2 | 0.819338           | 0.20746             | 0.50316             |
| PC3 | 0.562233           | 0.1417              | 0.64486             |
| PC4 | 0.5011             | 0.1254              | 0.77026             |
| PC5 | 0.300831           | 0.0748              | 0.84506             |
| PC6 | 0.252104           | 0.0623              | 0.90736             |
| PC7 | 0.223062           | 0.0545              | 0.96186             |
| PC8 | 0.137299           | 0.0333              | 0.99516             |
| PC9 | 0.081111           | 0.00329             | 0.99845             |
| PC10| 0.05579            | 0.00155             | 1                   |

$PW$ class of every record, location of the person and complete DisEnvi data to the cloud space. The selected PCs have made the acquired $Q'_{1000 \times 10}$ dataset as $Q'_{1000 \times 6}$ dataset, having six dimensions (PC1, PC2, PC3, PC4, PC5, PC6) accounts for 29.57, 20.75, 14.17, 12.54, 7.48 and 6.23%, respectively, and cumulatively 90.73% data, as shown in Table 5. The performance of the PCA has been compared with Singular Value Decomposition (SVD) by implementing SARIMA on the PCA- and SVD-summarized data, and on non-summarized data, as shown in Table 7.

The PCA-based dimensionality reduction of the aggregated data at the NFN has also optimized the data transmission energy consumption of the NFN ($E_{ET_{NFN}}$), and the NEI-processed received PanHealth records has optimized the data collection energy consumption of the NFN ($E_{EC_{NFN}}$). For determining the energy consumption of the DRecTrans operations of an NFN, the current evaluation has taken into account the specification of a rotary-wing UAV [65], where the UAV has employed ZigBee for data communication with the data rate of 9.6 Kbps, and consumed 23 m Joule for transmitting and receiving 56 bits. The evaluation has analyzed the data collection and transmission along with their corresponding energy consumptions at NFN, as shown in Fig. 5 (b) and Table 6. The results have depicted that the data aggregation by the NFN from 100 UFNs and 61 environmental sensors after data processing by NEI at UFNs and its transmission after data summarization at NFN have optimized the data collection and transmission, along with their corresponding energy consumptions, at ECL-hosted NFN with overall 26.66% data collection energy efficiency ($EE_{EC_{NFN}}$) and 28.13% data transmission energy efficiency ($EE_{ET_{NFN}}$).

3.4. Cloud-based Panic Severity Prediction Evaluation

The cloud space receives reduced dimensional PanHealth-DisEnvi data of the stranded persons along with their locations and $PW$ class. The cloud space also receives the geographical data of the disaster-affected area: status and location of DisEnvi sensors. The cloud space predicts PSI using SARIMA. The PSA layer employs the monitored PSI time-series to predict the future PSI of the stranded person using SARIMA. The current evaluation has implemented SARIMA in R-Studio, on
TABLE 6. DRecTrans data and energy consumption analysis at NFN.

| S.No. | Parameters | Received Values | Transmitted Values | $E_{R\_NFN}$ | $E_{T\_NFN}$ | $EE_{R\_NFN}$ | $EE_{T\_NFN}$ |
|-------|------------|-----------------|--------------------|--------------|--------------|--------------|--------------|
| 1.    | ECL        | 8229            | 10 220             | 346.82 mJ    | 430.73 mJ    | 26.66%       | 28.13%       |
| 2.    | Without ECL| 11 220          | 14 220             | 472.88 mJ    | 599.31 mJ    | –            | –            |

TABLE 7. PCA performance.

| Prediction | MAE     | RMSE    | MSE     |
|------------|---------|---------|---------|
| PCA-based SARIMA | 0.1257462 | 0.424595 | 0.1257462 |
| SVD-based SARIMA | 0.2563412 | 0.9623456 | 0.2563412 |
| SARIMA on non-summarized data | 0.1374462 | 0.454297 | 0.1374462 |

FIGURE 6. Prediction of PSI using SARIMA.

an Amazon EC2 instance, where SARIMA has used forecast package of R-language for predicting the PSI. To determine an accurate model for SARIMA, the PACF and ACF plots of PSI time series data have been examined, and found SARIMA (1,0,0)(1,0,0)[10] as the final model. Fig. 6 has depicted the PSI prediction for a particular time window. The efficiency of the employed SARIMA has been evaluated based on the three approaches of the data summarization: PCA, SVD and non-summarized data, as shown in Table 7. The evaluation has depicted that the SARIMA-based prediction on three approaches itself is highly accurate with having lower error rate; however, in comparison of all three, the PCA-based summarization has enabled the SARIMA for predicting PSI with least error. The overall result analysis has depicted that the SARIMA predicts the PSI with lower error, and with better efficiency along with PCA.

3.5. Disaster Mapping Efficiency

The DML builds an evacuation map based on the disaster status of the DisEnvi Sensors and identifies the critical regions using GPA of the stranded persons. A Java-based API for open street maps has been used for highlighting the disaster status and street status: passable or impassable, as shown in Fig. 7 (a and b). A Java-based API has been built to create regions and identify the criticality of the regions, using panic severity of the stranded persons through GPA. The identification of critical regions based on the different PSI class persons and region priority, and determination of evacuation priority of the person within those regions help in on-time and orderly evacuation of the stranded person. This can be well depicted from the performance analysis of the critical region map, as shown in Fig. 7 (c), which has determined that the region R23 is having the highest region priority, followed by R24 and R8. If there does not happen any identification of critical regions, and if an evacuation team has to evacuate persons from the specified area, as shown in Fig 7, they will traverse sequentially in each region and might evacuate persons from R3 first (if the team enters from North-West), or from R6 (if the team enters from South-West) or from R38 (if the team enters from South-East), or from R34 (if the team enters from North-East), which will result in the evacuation of lesser panicked persons first. However, the identification of critical regions guides the evacuation team first to evacuate persons from R23, followed by R24, R8, and so on. The results have depicted that the DML facilitates an efficient on-time and orderly evacuation of the stranded persons based on their panic health.

4. CASE STUDY OF COVID-19 BASED PANIC

The proposed CPS has a vivid scope for disaster-oriented panic in different situations. One such disastrous situation nowadays faced by the entire humankind is the COVID-19 pandemic. COVID-19 is an infectious disease which was first diagnosed in Wuhan, China in December 2019. It has spread globally in such a short period that the World Health Organization (WHO) [64] had to announce it a global pandemic. Till the date (as of 08 September 2020), the WHO [65] has reported 27 236 916 confirmed cases, and 891 031 causalities in more than
200 countries. The areas like Wuhan (China), Madrid (Spain), New York (United States), and alike, where a large number of infected cases has been reported, have presented many new challenges viz. optimal stocks of healthcare equipments, availability of medical staff, tracing of infected persons, arrangement of quarantine facilities and panic among the infected and other people.

The proposed CPS can be used in various COVID-19 related situations viz. panic monitoring, panic prevention and selective testing. It has been found that the people are hiding their symptoms to avoid quarantine and contributing in the transmission of the infection. Surprisingly, the relatives of such persons are helping them and becoming the principal targets of infection transmission. The proposed CPS can monitor the panic health of the persons in different regions and can relate the panic among persons with such scenarios, and arrange COVID-19 testing for them. The system can contribute an additional dimension to the set of guidelines for selective COVID-19 testing. Also, the system can monitor the panic health of the persons to prevent any panic health-related issues during this distressing period of COVID-19 outbreak.

5. CONCLUSION

In this paper, a fog-assisted energy-efficient CPS has been proposed, which facilitates the panic-based evacuation of the stranded persons. The main contribution of the presented CPS is the energy consumption optimization of the DRecTrans operations through fog-assisted two-factor data reduction, and panic severity-based GPA for identifying the critical regions. The presented system has efficiently conserved the DRecTrans energy of the fog nodes using data reduction approaches: NEI and PCA, SARIMA-based panic severity prediction at the cloud space, and GPA-based panic severity-oriented identification of the critical regions. The proposed system has efficiently addressed the evacuation-related challenges irrespective of the nature of the disasters and explored the panic-oriented evacuation in the domain of smart environments. The paper has also discussed the vivid scope of the proposed CPS through a case study of COVID-19 based panic for tracing infected persons, selective testing and panic prevention.

DATA AVAILABILITY

The data underlying this article will be shared on reasonable request to the corresponding author.

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