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Smart internet of things (IoT) based healthcare framework environment for Chikungunya disease diagnosis

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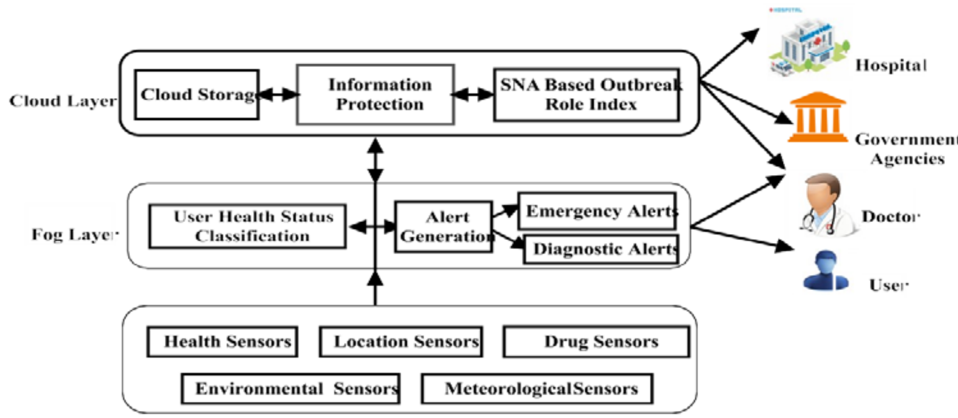
Article

ABSTRACT

This paper reports a Fog-based health monitoring systems framework to enable the real-time tracking and analysis of users' health data and associated events. This framework encompasses a broad spectrum, including medical, environmental, meteorological, and location-based information, with the overarching goal of addressing the escalating threat posed by different pathogens, mainly the rapidly spreading chikungunya virus (CHV) worldwide. The chikungunya virus, transmitted by Aedes aegypti and Aedes albopictis mosquitoes, raises significant public health concerns. The paper outlines three potential modes of virus transmission: 1) infection from infectious female mosquitoes, 2) transmission to healthy female mosquitoes from infected individuals, and 3) contagious female mosquitoes laying infectious eggs. In response to the challenges in identifying and preventing chikungunya virus outbreaks, the paper introduces strategic measures. Key objectives include establishing a Fog-based system that leverages user health symptoms and environmental factors for remote CHV diagnosis, delivering instant diagnostic and emergency notifications to users for timely responses, computing metrics from Social Network Analysis (SNA) graphs to depict virus contraction or transmission likelihood, generating warning messages for government and medical organizations to contain outbreaks, and safeguarding users' sensitive information against unauthorized access. In essence, the designed Fog-based health monitoring approaches seek to achieve comprehensive real-time monitoring and analysis, providing a systematic framework for CHV diagnosis, notification, and containment.



Keywords: Fog computing, Cloud layer, Fog layer, Health sensor, Location sensor, Environmental sensor, Meteorological sensor

INTRODUCTION

The most quickly spreading contagious virus, chikungunya, is posing a growing threat to public health around the world.[1] Both Aedes agypti and Aedes albopictis, two species of infected mosquitoes, are the means by which it enters the human body. There are three methods by which this virus might spread. 1) Chikungunya virus (CHV) can infect people when it is transmitted by infectious female mosquitoes. 2) It can be spread to healthy female mosquitoes by infectious people. 3. Contagious female mosquitoes are capable of laying contagious eggs. In Tanzania, it was initially discovered in 1952. The World Health Organization reports that the Pan American Health Organization regional office received reports of 3,49,936 suspected cases and 37,480 confirmed cases of chikungunya. Among these, there were 2,65,000 suspected cases from Brazil, over 1700 cases from Kenya, and 19,000 cases from elsewhere. There are 60 countries in Africa, Asia, America, and Europe where CHV has been detected. Chikungunya shares many of the same symptoms as dengue and the zika virus, including fever, joint pain, headache, muscle soreness, red eyes, nausea, and rash. Table 1 shows a comparison based on symptoms that helps distinguish CHV from dengue and zika viruses. Table "+++" lists the major symptoms of the dengue, zika, and chikungunya viruses; "++" lists the less common but still significant symptoms of these viruses; "+" lists the very infrequent symptoms that may or may not

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appear in a person afflicted with these viruses; and "-" lists the symptoms that are absent in a person suffering from these viruses.

Table 1 Symptoms Based Comparison of Dengue, Zika and Chikungunya Virus

Symptoms	Dengue	Zika	Chikungunya
Fever	Sudden onset of high fever (39° to 40°C)	Low grade fever (less than 38.5°C)	Abrupt onset of high fever (over 39°C)
Headache	+++	+++	++
Skin Rash	+++	+++	++
Joint Pain	++	++	+++
Muscle Pain	++	+ +	++
Red Eyes	-	+++	+
Bleeding Disorder	++	-	-
Pain Behind Eyes	+++	+	-
Onset Post Infection	4-7 days	3-12 days	2-7 days
Nausea	+++	+	+
Abdominal Pain	+++	-	-
Itching	++	+++	+/-
Sore Throat	-	+	+
Fatigue	+++	+++	+

In order to contain an outbreak in real time, remote detection and monitoring of infectious illnesses is becoming increasingly important. These kinds of illnesses are too strong to manage with the current healthcare infrastructure. The lack of accessibility to diagnostic tests, the inability of individuals to provide essential information about their health and environmental situations, and the use of outdated methods for proactive disease monitoring and diagnosis are only a few of the drawbacks of the current systems. There are situations when a patient is unable to come to the hospital for a normal examination or when doctors are unable to examine every patient on a regular basis. Therefore, in order to provide healthcare support services, a remote monitoring system is required.

The development of wearable wireless sensors, cloud computing, and mobile technologies has spurred different approaches to cloud-based healthcare services. Context-aware and mobile technologies are even being used to shift a variety of healthcare applications to cloud platforms, which enable real-time services at remote locations.[2] These systems have numerous difficulties, including transmission of large data, location awareness, and latency issues. Big data transmission via a network increases the likelihood of error since it involves sending a lot of data for processing, which increases network traffic congestion. A single data transmission error in an emergency situation results in an incorrect diagnosis and a delay in notifying the user.

A number of advantages, including efficient resource use, quality assurance of services, timely access to medical data, and prompt emergency notification, are made possible by the use of fog computing in Internet of Things-based healthcare systems (Ahmad,et.al.[3]). These significant advantages promote the usage of fog as a mediator layer between IoT sensors and the cloud computing layer in order to determine the CHV category and to promptly create real-time notifications for end users.

A strategies are put forth in this paper to overcome the difficulties in identifying CHV and preventing outbreaks. The following are the main goals of the methods this paper suggests:
(i) To create a fog-based system that uses the user's health symptoms and the environment around it to provide a remote diagnosis of CHV.

(ii) To provide users with instant diagnostic and emergency notifications so they may respond appropriately and on time.

(iii) To compute several metrics derived from Social Network Analysis (SNA) graphs to illustrate the likelihood of contracting or spreading the virus. (iv) To produce warning messages for government and medical organizations in order to contain the outbreak in areas that are at danger and have been infected. (v) To protect users' sensitive information to prevent unwanted access.

Fog-based health monitoring approaches are suggested for real-time monitoring and analysis of users' health statistics and related events, including medical, environmental, meteorological, and location-based data, in order to accomplish these goals.

RELATED WORKS

Shah, et.al.[4] outlined the obstacles needed to achieve a wide range of quality of service targets for healthcare monitoring cyber-physical framework. Costanzo, et.al[5] report a secure health management device for a remote patient. It will utilize ontological structure for evaluation, and fuzzy rule will promote the method in case of an emergency health situations. Nandyala et.al.[6] introduced a smart home monitoring arrangement with the aid of fog computing that is located at the edge of the cloud. Oluwagbemi, et.al.[7] offered a data-driven framework to treat the Ebola care guidance. Recently, Sood, et.al.[8] suggested a cyber-physical device of fog and cloud storage to reliably track malaria and dengue-transmitting mosquitoes. Hassan et.al.[9] discussed case study of six Bangladesh patients who were suffering fromChikungunya Virus (CHV). Discovery of CHV in East Africa, its emergence in Western hemisphere, and outbreak in Asia before 2004 is represented by Weaver, et.al.[10] They also compared CHV with other mosquito borne viruses. Gobbi et.al.[11] represented emergence of chikungunya in different continents from Africa to the Americas. Peper et.al.[12] presented a case report of 39 year old African-American female infected with CHV. Liuand Stechlinski, et.al.[13] developed a new model to control the spread of chikungunya infection with time varying parameters. They considered three types of control schemes namely, mechanical control of mosquito breeding sites, reduction of contact rates between humans and mosquitoes, and pulse vaccination of human. Entomological survey is conducted by Jain et.al.[14] on Aedes mosquitoes to evaluate vertical transmission of

CHV in adult and immature field populations of Aedes Agypti in the state of Delhi and Haryana (India). Container index and minimum infection rate are also calculated to control the vector transmission and expansion. Calvo, et.al.[15] developed nested-PCR protocol for detection of dengue virus, chikungunya and zika virus infection in the febrile patient samples. Murugan and Sathishkumar, et.al.[16] described structure, vector, symptoms and signs of CHV. They described various tools to diagnose this virus, treatment and precautionary measures to reduce the density of virus. Silva, et.al.[17] described clinical and laboratory methods to make diagnosis distinction among dengue, zika and chikungunya. They provided treatment and preventive measures to control the outbreak of these viruses. Pabbaraju, et.al.[18] developed multiplex real time reverse transcription polymerase chain reaction for simultaneous detection of zika, chikungunya and dengue virus from patients with symptoms of arboviral infection.

Lai X, et. al.[19] conducted a survey on-body sensor networks tolist the current development and challenges in different sectors. The applications of the Body sensors network were also presented. The authors also mentioned that there were still problems in existing frameworks, and the depth study could resolve them.

Archambault et. al.[20] examined the case study on Collaborative writing applications - CWA. Wikis and Google Documents were real-time examples of CWA. The case studyevaluated the objectives of CWA like assessing the process, exploring cost-effectiveness, and searching for the CWA effect.

Xesfingi et. al.[21] surveyed the satisfaction level of the patientfor medical treatment between 2007 to 2012. Thirty-one countries were added for this study. The result concluded thatthere is a strong relationship between health care services andpatient's satisfaction. Moreover, the association of medical experts and patients was highly correlated.

Barjis et. al.[22] suggested a health care model in South Africato fulfill the requirements of healthcare services. The proposed model would benefit the people who are living in rural areas. Moreover, it would also be beneficial to fight against the poor delivery of health care assistance.

Jain et. al.[23] recommended architecture of healthcare systems based on security and privacy. The proposed architecture was prepared by reviewing the existing works. The main aim of the project was to protect the health care datasince IoT devices generate huge amounts of data.

Sruthi et. al.[24] conducted a comprehensive review forobserving the health of rural areas. The prime objective behind this survey was to be aware of the current situations of remote patient monitoring. A couple of researchers proposed a system to reduce the need for personal computers while treating the patient using a GPS-enabled smartphone. Cryptographic operations added for the security and privacy of health care records. The system suggested the prime objectives of reducing cost and improving health care quality.[25]

A couple of researchers suggested the optimized model of the wireless access network architecture during patient monitoring. The study was conducted in the healthcare segment against the challenges of eHealth resource flexibility and cost.[26,27]

DESIGNED FRAMEWORK

The overall working of proposed approaches is shown in Figure 1. Fog-based health monitoring approaches are suggested for real-time monitoring and analysis of users' health statistics and related events, including medical, environmental, meteorological, and location-based data, in order to accomplish these goals.

The designed approaches comprise of three layers, namely, wearable IoT sensor layer, fog layer and cloud layer.

Wearable IoT Sensor Layer

The Internet of Things sensor layer is in charge of gathering information on symptoms connected to health as well as different user-related events that occur inside and outside of the environment. The information gathered encompasses health, environmental, pharmaceutical, location-based, and meteorological data. Data is gathered from the wireless hardware devices that are incorporated into the user's body and from the areas inside and outside of the user. Real-time data transmission and sensing are capabilities of these gadgets. An overview of the several sensors used to track users' health indicators and related events is given in Table 2. The fog layer receives the values of all these characteristics in order to categorize the user's health. The following is a full explanation of the dataset:

Health Data: Vital indicators of a user's health make up the health data set. This kind of dataset comprises symptoms including a high fever, sore throat, exhaustion, red eyes, body rashes, joint pain, headache, body discomfort, and stomach pain. The user's body has a variety of implanted health sensors to collect this kind of information.

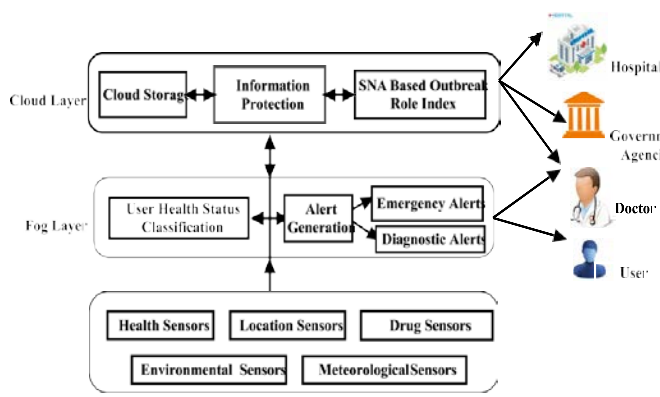


Figure 1: Overview of designed system

Environmental Data: This dataset takes into account user-provided information regarding mosquito breeding areas and dense populations. Wireless mosquito sensors positioned at various locations continuously record this data. Sensors analyze the air temperature, humidity, carbon dioxide, and temperature near standing water in ponds, lakes, dams, rivers, tube wells, refrigerators, coolers, and air conditioners to assess the conditions that mosquitoes may deposit their eggs in. Numerous sensors inserted in various locations throughout the house and its environs also detect water flow rate and sewer quality.

Medicinal Data: Medicinal data includes the user's drug regimen. It includes the name, form, quality, and duration of the medicine's intake that are all part of the user's pharmaceutical regimen. RFID tags, or radio frequency identification, are used to collect this data. The gateway to this dataset annexes time in a trivial method.

Location Data: It covers where mosquito breeding and dense places are located, as well as the locations of exposed, uninfected, susceptible, and infected users. Global Positioning System (GPS) sensors pick up these places to gather each user's trip history while they are infected with CHV. The close interactions between susceptible, exposed, infected, and uninfected people, as well as mosquito breeding grounds, are also recorded using RFID tags and mosquito sensors.

Meteorological Data: It contains information about the climate, such as humidity, rainfall totals, and maximum and lowest temperatures. Different climatic sensors pick up on these.

Table 2 Dataset of Various Events

S. No.	Data Set	Attributes	Wireless Sensors
1	Health Data	Fever, Body Pain, Rashes on Body, Red Eyes, Headache, Nausea, SoreThroat, Muscle Pain and Fatigue	Body Sensors
2	Environmental Data	Water quality, Air Temperature, Humidity, Carbon Dioxide, Mosquito Density	Water Quality Detector Sensor, Climate Sensor Mosquito Sensor
3	Medicinal Data	Strength, Type, Form, Proportion	RFID Tag
4	Location Data	Location of Mosquito Dense Sites, Mosquito Breeding Sites, Time	GPS Sensor
5	Meteorological Data	Maximum Temperature, Minimum Temperature, Rainfall, Humidity	Climate Detector Sensor

Fog Computing Layer

Between the cloud computing layer and wearable IoT sensors, the fog computing layer serves as a link. The gathered data from Internet of Things (IoT)-based sensors is processed and analyzed in real time using it. It instantly notifies or alerts the user in real time about the CHV classification category depending on their medical symptoms. The cloud layer is further connected to this system in order to store, analyze, and compile each user's medical record.

Fog computing layer consists of two components such as user health status classification and alert generation. The description of both components is as follows.

User Health Status Classification Component

When making decisions about different medical diagnoses, a categorization is a crucial tool. By employing the Fuzzy C Means (FCM) classifier to categorize people as likely sick or uninfected based on their CHV attribute values, this component gives users an initial diagnosis. According to Zhang, et. al.[28] FCM is a data clustering technique that divides a dataset into n clusters, each of which has a distinct degree of affiliation with each data point. A given data point has a high degree of membership or belonging when it is located close to the cluster center, and a low degree of membership when it is located far from the cluster center.

A set of ten data points are denoted as Y= {Y_1, Y_2, Y_3, Y_4, Y_5, Y_6, Y_7, Y_8, Y_9, Y_{10}} where this Y_1, Y_2, Y_3, Y_4, Y_5, Y_6, Y_7, Y_8, Y_9, Y_{10} refers to the attributes i.e. fever, joint pain, headache, muscle pain, red eyes, skin rash, nausea, sore throat, itching and fatigue. Two fuzzy clusters, S_1, and S_2 are the subset of all possible fuzzy subsets of Y which are used to classify users by grouping their dataset into two clusters in which one cluster contains uninfected users and second cluster contains possibly infected users. The main objective of FCM is to minimize errors in the objective function. The mathematical form of the objective function is shown in Eq. 2.1 and Eq. 2.2.

$$J(U, A, Y) = \sum_{i=1}^{2} \sum_{j=1}^{10} u_{ij}^{m} \, d_{ij}^{2} \, (yj, \; ai) \quad \ldots\ldots 2.1$$

$$J(U, A, Y) = \sum_{i=1}^{2} \sum_{j=1}^{10} u_{ij}^{m} \, ||yj - ai||^{2} \quad \ldots\ldots 2.2$$

Where 'U' is the partition matrix such that U = u , i = 1,2 and j = 1,2….10. 'u ' is the membership value of the j[th] data to the i[th] cluster. 'Y' is the set of data points. 'A' is the set of cluster centers A = a_i. 'm' is the fuzzy strength parameter and is generally chosen as 2 for optimal statistical results. It controls the fuzziness of the system. $||y_j - a_i||^2$ is the Euclidean distance between data points 'y_j' and cluster centers 'a_i' of the i[th] cluster. Following three conditions ofmembership value must satisfy.

Range of membership values between 0 and 1 is given in Eq. 2.3

$$u_{ij} \;\; \epsilon \, [0,1] \; \forall \; i,j \quad \ldots\ldots \; 2.3$$

The summation of membership values of each data point must be 1 as given in Eq. 2.4

$$\sum_{i=1}^{2} Uij = 1 \; ⍰ \, j \quad \ldots\ldots 2.4$$

The summation of all membership values in each cluster must be lesser than a number ofdata points (N) as given in Eq. 2.5.

$$0 \quad < \sum_{j=1}^{10} Uij \; < \; N \quad \ldots\ldots 2.5$$

The details of the FCM algorithm are presented in Algorithm 1. An Algorithm 2 is designedto evaluate the category of the user using FCM classification algorithm.

Algorithm 1: Fuzzy C-Means algorithm

Step 1: Determine the number of clusters and also set the value for the fuzzifier constant. Threshold value (ε>0) of the termination condition is also to be assigned which is to be used for process termination.

Step 2: Initialize the membership matrix

U = [ ] c*n where c is number of clusters and n is the number of data points.

Step 3: Calculate fuzzy cluster centers a_i using following Eq. and k is the iteration number

$$a^k = \frac{\sum_{j=1}^{n} [u_{ij}^{(k-1)}]^m y_j}{\sum_{j=1}^{n} [u_{ij}^{(k-1)}]^m} \quad \text{where } i = 1,2....c$$

Step 4: Update membership value $\mathbf{u_{ij}}$ with $\mathbf{a^k}$ using following equation

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{||y_j - a_i||}{||y_j - a_k||}\right)^{\frac{2}{m-1}}}$$

Step 5: Update membership matrix U^k and U^{k+1}

Step 6: If $|| U^{k+1} - U^k || < \varepsilon$, stop otherwise increment k to follow step 3.

This process for solvingmembership degree and cluster centers continuous until termination condition is satisfied.

Algorithm 2: To evaluate the health symptoms of user to classify category

Input: CHV health attributes and identification number of user
Output: Classified user's category based on health attributes

Step 1. Get CHV health attributes and identification number of userStep 2. If identification number is already present in database

Step 2.1 Record with newly generated data will be updated

Step 3. Else

Step 3.1 A new record with user's identification number will be created and health attributeswill be stored.

Step 4 Execute FCM to predict the category of the user

Step 5. Store classified category of user in the database with corresponding identification number

Step 6. Exit

Alert Generation Component

The alert generation component is in charge of instantly sending alert messages to the user's mobile device. There are two types of alerts included in it: emergency and diagnostic. All users, whether they are potentially infected or not, receive diagnostic notifications. Emergency alerts, on the other hand, are only generated for those who may be infected during an emergency. The way in which diagnostic and emergency alerts operate in detail is as follows:

Diagnostic and Emergency Alerts:

This component will instantly send a diagnostic alert message to the user's mobile device upon diagnosis. The diagnostic alert message indicates whether the user is potentially infected with or not. When a user is identified as potentially having CHV infection, they are closely observed for a variety of factors, including location, medication, surroundings, and temperature. The sensitivity factor in this instance with regard to the timing of several occurrences is determined as follows:

$$\text{Sensitivity Factor} = P\left(\frac{S}{E_1 \cup E_2 \ldots\ldots\ldots E_n}\right) \quad .... \quad \mathbf{2.6}$$

Where S denotes the user health category infected as CHV. $\{E_1, E_2 \ldots E_n\}$ represents the probability of occurrence of 'n' events in current time.

An automatic notice is provided to the concerned user to take the necessary steps towards wellness if the sensitivity factor of the afflicted user exceeds a predetermined threshold. In addition, it gives users information about hospitals in the area based on their location and notifies local physicians of their infection status so that a CHV test may be done right away. The patient's threshold value is predetermined in light of the patient's medical history and condition. If the sensitivity factor is less than the threshold, no warning is generated on the user's mobile device. In the event of a patient emergency, these warnings can also be shared with physicians and other healthcare providers via cloud storage. As a result, sensitivity factor-based alert creation improves a doctor's ability to make decisions in a time sensitive manner and reduces the number of false alert generation. Overall working of emergency alert generation is depicted in Algorithm 3.

Algorithm 3: To generate emergency alerts to users, doctors and healthcare professionals

Input: Current classified category of user, probability of various events and predefined threshold value

Step 1. Get classified category of user, health attributes and events of user of current time stamp

Step 2. If classified category = possibly infected category

Step 2.1 Calculate Sensitivity Factor of possibly infected user and probability of variouseventsof current time stamp.

Step 3. If (Sensitivity Factor > Predefined Threshold)

Step 3.1. User is in unsafe state and immediate emergency alert is generated on user's mobilephone.

Step 4. Else

Step 4.1. user state is safe and no alert is generated to user

Step 5. Exit

Cloud Layer

Cloud layer consists of three components namely; cloud storage, SNA based outbreak role index and information protection. The following subsections will discuss in detailsabout these components.

Cloud Storage

The purpose of cloud storage is to hold data about users who may be infected or not, as well as the locations of mosquito breeding grounds and dense populations. It has a massive amount of storage to keep analytical results safe. Each user's medical information is compiled, and it is safely shared with users, pharmacies, hospitals, and other healthcare providers in addition to approved medical personnel. The fog layer also generates diagnostic and emergency alarm signals, which are saved on cloud storage for later examination by specialists so they can respond quickly and take preventative measures in case of an emergency. Cloud storage is used to store travel data from both infected and uninfected users in order to develop or update the global SNA graph and produce warning notifications as needed. Government aided healthcare centers can also upload data as well as any information regardingfirst aid, free camps, etc. to control the outbreak of CHV.

SNA Based Outbreak Role Index

Because mosquitoes have a very restricted range of flight, people can spread the CHV virus over great distances or from one location to another. Mosquitoes and humans are both considered infectious and in good health. There are three methods by which this virus might spread. 1) Female mosquitoes carrying the CHV virus can infect healthy humans. 2) Healthy female mosquitoes can contract it from infected humans. 3. Contagious female mosquitoes are capable of laying contagious eggs. Numerous instances of viruses spreading within the same location or from one to another exist

Case 1. Human Infection in region ‘i’ take place when infected mosquitoes living in region ‘i’bites a healthy person who is:

Resident in region ‘i’ and present in region ‘i’.

Resident in region ‘j’ and present in region ‘i’.

Case 2. Mosquito infection in region ‘i’ take place when a susceptible mosquito bites an infectedperson who is:

Resident in region ‘i’ and present in region ‘i’.

Resident in region ‘j’ and present in region ‘i’.

By providing alert messages to the user and recommending CHV control actions to government agencies, this component seeks to identify locations that are infected and prone to risk in order to manage and control the CHV infection outbreak. SNA is utilized to determine the affected and risky areas.[29] It offers a range of methods and instruments for deciphering and interpreting intricate graphs. If a social network graph is effectively constructed, then SNA tools and techniques are valuable. Consequently, Algorithm 5 offers a step-by-step computation for the creation of a global SNA graph. This graph uses GPS-enabled mobile phones to track a user's travel locations once the person is deemed to be potentially infected by the classification component. These areas have been included.

When designing a SNA graph, as demonstrated in Figure 2(a), different color schemes are also employed for different areas and users. Yellow indicates areas that are at danger, green indicates uninfected areas and uninfected individuals, and red indicates infected regions and possibly infected users in the SNA graph. The areas where one or more people are affected are known as infected regions. Areas without any CHV infections are known as uninfected zones. Risk-prone areas are ones where there is a high chance of contracting CHV infection from one or more infected people who visit

Algorithm 4: To create global SNA graph

Input: Infected or Uninfected user, their resident and travelling historyOutput: Newly or updated global SNA graph

Step 1. Get classified category of user, resident and travelling locationsStep 2. If user classified category = Possibly infected Then

Step 2.1 Create two nodes one for user and second for his/her residence with Red color

Step 2.2 Get travelling locations of user

Step 3. Else

Step 3.1 Create a new node of user’s residence with Green color

Step 3.2 Get travelling locations of user

Step 4. For i = 1 to n // n is the number of regions in SNA graph

Step 4.1 if travelling location [i] is already in the graph

Steps 4.1.1 create a new edge between travelling location [i] and user. Update color ofregions according to the category of user

Step 4.2 Else

Step 4.2.1 create a new node with travelling location [i]

Steps 4.2.2 create an edge between travelling location [i] and user. Update color ofregion according to the category of user.

Step 5. Exit

Many important outputs can be drawn from global SNA graph which will help government health agencies to control the CHV outbreak in infected regions. There are several outbreak metrics which can be computed from SNA graph. These metrics are explained below:

Metric 1: Outbreak Role Index (ORI)

ORI calculates the probability of any user to receive or spread the infection. It is calculated fromSNA graph.

Definition1*:* ORI for infected user and infected regions states the ratio of number of infected regions visited by infected user to the total number of regions visited by infected user.

Definition2: ORI for infected user and uninfected regions states the ratio of number of uninfectedregions visited by infected user to the total number of regions visited by infected user.

Definition3: ORI for uninfected user and infected regions states the ratio of number of infectedregions visited by uninfected user to the total number of regions visited by uninfected user.

There are some cases which will require special attention of healthcare agencies.

• When the ORI for an infected person or region is high, it indicates that the user or region needs to be investigated as soon as possible. Users' mobile devices and government organizations should receive warning alerts so they may take appropriate steps to contain the outbreak.

• When the ORI is high for both infected users and uninfected regions, it indicates that the infected user visited a lot of uninfected areas. Thus, there is a good chance that this user may infect others with CHV. Quarantining these users as soon as possible is therefore necessary. In order to manage the CHV outbreak, warning notices should be disseminated to the local hospitals and government agencies in risky areas.

• When an uninfected user visits a lot of contaminated places and their ORI is high, it indicates that they are at a very high risk of becoming infected. Thus, these kinds of users should receive an alert right now.

Metric 2. Relative Score of Each Region

Critical regions from the global SNA graph can be identified with the aid of each region's relative score. On the basis of the score values, pertinent alerts may be generated. The government agencies will be able to identify crucial areas and stop all travel to and from those areas with its assistance. To stop the CHV outbreak in that vital area, government organizations can take preventative action.

Relative score S_i of any region i can be computed as

$$S_i = 1/\lambda \sum_j U(i)\, Sj \quad \frac{1}{\lambda} \sum_{j=1}^{n} Aij * Sj \quad \ldots\ldots\ldots\ldots 2.7$$

Where U(i) is the set of infected users nodes which are connected to the i^{th} region. 'λ' is the Eigenconstant and 'A_{ij} ' is the adjacency matrix. A region with high score should be quarantined as early as possible.

These metrics are used to identify the risk level of CHV in potentially infected and risk-prone areas. Those who live or visit these areas can receive timely alerts and suggestions for infection control based on the risk level of CHV infection. These regions are mapped on the Google map web service. Figures 2(b) and 2(c) illustrate the use of hexagonal based mapping to depict areas that are at risk and those that are infected. The regions of newly infected users and their travel history are represented by a unique color scheme that is effectively based on the density of potentially infected users as well as the density of infected visitors visiting in any given region, as provided in Table 3.

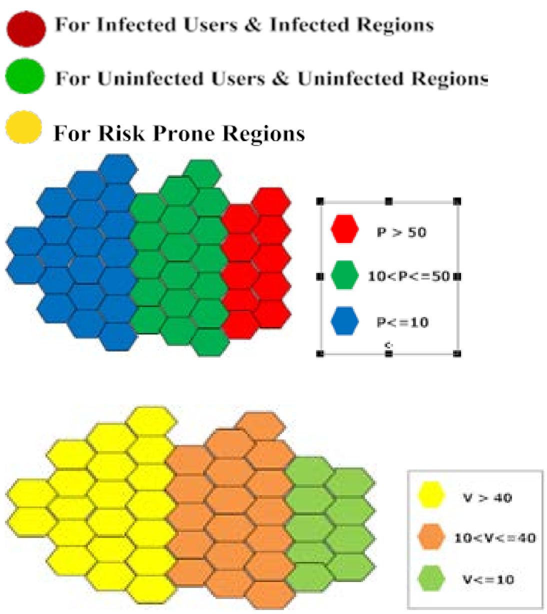


Figure 2 (a) Coloring Scheme for Users and Regions in SNA Graph (b) Hexagonal Representation of CHV Infected Regions (c) Hexagonal Representation for CHV Risk ProneRegions.

Table 3 Different Risk Level of CHV for Infected and Risk Prone Regions

Levels of CHV Infection for Infected Regions		Levels of CHV for Risk Prone Regions	
Infected population (P) in %	Risk level (Color)	No. of infected visitors (V) in %	Risk level
P>50	High (Red)	V>40	High (Dark Yellow)
10<P<=50	Medium (Green)	10<V<=40	Medium (Orange)
P<=10	Low (Blue)	V<=10	Low (Light Green)

Information Protection

User health and personal information is stored in a cloud storage component. It contains certain extremely private information that should not be disclosed to everyone. People may experience panic even if they unintentionally reveal such attributes to an unauthorized person. In order to prevent unauthorized access to data, the proposed system uses a two-stage information protection mechanism that consists of information fragmentation and key sharing. The following explains each step:

Information Fragmentation:

During this phase, user data is divided into three segments with different security levels: level 1, level 2, and level 3. Level 1 is very private and includes information about an individual's age, name, gender, mobile number, and residential address. Level 2 comprises of meteorological and environmental attributes information at a medium level. The least sensitive level of information pertaining to characteristics associated with CHV symptoms is Level 3. Even if level 3 data is obtained, it is impossible to pinpoint the user's precise identity. To retrieve the precise identity of the user, one must be aware of all three levels of fragments. Information was gathered in order to address the issue of safeguarding the user's extremely sensitive characteristics. To correctly fragment the data table, the following constraints should be met.

$F_1 \cup F_2 \cup F_3 = D$ 2.8

$F_i \cap f_j = \emptyset, i \neq j$ and $F_i, F_j \in F$ 2.9

Key Sharing Mechanism:

A data table 'D' contains sensitive attributes i.e. a_s should be protected from unauthorized users. So, key sharing mechanism is used to distribute the values of highly sensitive attribute into 'n' parts i.e. v_1, v_2, v_3 …vn. These `n' pieces are stored on different secure cloud servers. Choose k-1 coefficients $a_1, a_2 \quad a_{k-1}$ and assign key value a_s to the coefficient a_0.

Polynomial of degree (k-1) is represented in Eq. 2.10.

$F(x)=a_0+a_1x+a_2x_2+\ldots..a_{k-1}x_{k-1}$ 2.10

Choose secret keys $X = x_1, x_2\ldots\ldots x_n$ which are randomly chosen values corresponding to eachcloud server. System calculates each cloud server share by substitute the value of $x_i \in X$ and values of the coefficients a_1, a_2... a_{k-1} in Eq. 2.10 as $F(x_i)$ and store it to the corresponding cloudserver. To recreate the original value of highly sensitive attribute from key value of shares, knowledge of any `k' pieces where k<=n along with secret information i.e. $x_1, x_2\ldots\ldots x_n$ is required. The secret information is only stored on the trusted server, thus only trusted server can recreate the original value of highly sensitive attribute after retrieving at least `k' shares from any`k' cloud servers. Knowledge of any `k-1' or fewer pieces is not enough to recreate the originalvalue of attribute even if secret keys X is known to cloud servers.

Algorithm 5: To map infected and risk prone regions on Google map

Input: SNA graph

Output: Create or update Google map

Step 1. Identify possibly infected and risk prone regions from SNA graph.

Step 2. For every possibly infected region

Step 2.1. Calculate whole population and infected users in hexagonal structure of that region

Step 2.2. Increment the density of hexagonal structure

Step 2.3. Update hexagonal structure's color based on computed hexagonal's density, represented in Table 3.

Step 2.4. Plot hexagonal on Google map.
Step 3. For every risk prone region
Step 3.1. Calculate a total number of infected visitors visited in risk prone region.
Step 3.2. Increment the density of hexagonal
Step 3.3. Update hexagonal structure's color based on computed hexagonal's density, represented in Table 3.
Step 3.4. Plot hexagonal on Google map.
Step 4. Exit

RESULTS AND DISCUSSION

Generation of Symptoms Based Datasets

Symptoms based dataset to evaluate proposed system is systematically generated so that no possible case has been left out. Table 4 shows the probabilities of each CHV symptoms to be present in any new generated case while creating dataset for CHV. A real dataset of 5000 cases containing environmental attributes are obtained from (DHS Program Demographic and Health Surveys, (2017a , b)) and monthly climate attributes, namely temperature, humidity and rainfall are obtained from (UN Data: A World of Information, (2017a, b, c)) which are integrated systematically with the generated all possible cases of CHV infection related attributes. All possible cases of CHV infection related attributes are mapped randomly with the dataset of environmental and climate attributes as shown in Algorithm 6.

Table 4 Probabilities for CHV Symptoms

Primary Symptoms		**Secondary Symptoms**	
High Fever	0.18	Red Eyes	0.11
Joint Pain	0.15	Nausea	0.09
Skin Rash	0.11	Itching	0.08
Headache	0.09	Sore Throat	0.07
Muscle Pain	0.08	Fatigue	0.05
No Symptoms	0.40	No symptoms	0.60

Algorithm 6. To create synthetic data sets for CHV

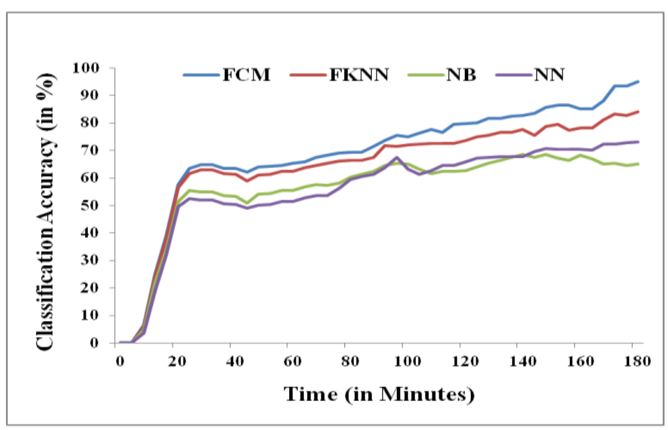
Input: Data containing CHV symptoms, datasets of environmental, climate attributes and number of distinct cases required.
Output: Generate CHV datasets
Step 1. 'n' be the number of CHV cases initialized with 1.
Step 2. For n <= required number of cases
Step 3. Assign values to primary symptoms based on probabilities in Table 6.
Step 4. Assign values to secondary symptoms based on probabilities in Table 6
Step 5. Create a new case by combining all CHV symptoms values with environmental and climate attributes.
Step 6. If new case is already present in database then
Step 6.1. Discard the new case
Step 7. Else
Step 7.1. Add the new case and value of generated cases is increased by 1
Step 8. Exit

Data Transmission to Fog Layer

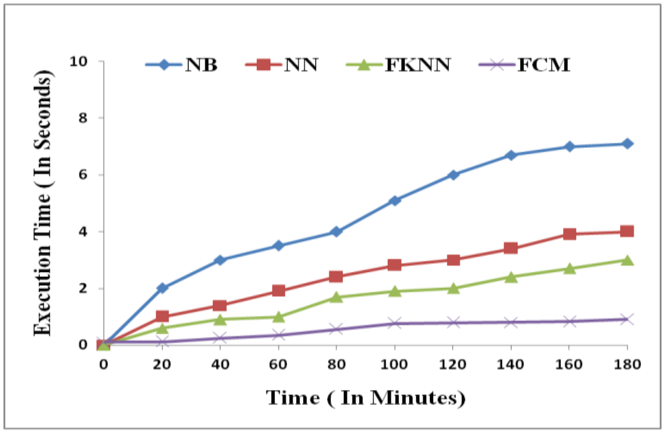
The FCM clustering algorithm is trained and tested on generated datasets in order to classify users as either possibly infected or not. Using Matlab running on Windows 7, the FCM classifier was implemented on an Intel i7 CPU running at 2.50 GHz with 4 Gbytes of memory using a dataset of 5000 cases. Prior to calculation, the dataset is normalized to convert symptoms that are accepted as "yes" or "no" values into the interval [0,1] based on the severity of each symptom. This helps to prevent numerical issues. Fuzzy strength parameter "m," which varies within the range [1,2], is used to test the FCM algorithm's classification accuracy. We test the following statistical parameters: recall, accuracy, precision, sensitivity, specificity, and error rate—for every choice of'm'. Table 5 illustrates how closely the classification performance of the FCM classifier with varying values of the'm' parameter is performed. However, "m"=2 yields the best accuracy. Based on high classification accuracy, sensitivity, specificity, precision, recall, and low error values, the results demonstrate that the system can effectively classify users as possibly infected or uninfected. Figure 3 compares several classification algorithms, including Naïve Bayes (NB), Fuzzy K-Nearest Neighbors (FKNN), and Neural Network (NN), using varying numbers of cases. The results of the classification algorithms are displayed in Figure 3(a), where the FCM based classification algorithm outperforms the other algorithms in terms of accuracy. Figure 3(b) displays how long it takes for various. It is because fog computing provides various resources such as compute, storage and communicationin the close proximity of mobile users as compared to cloud computing. It also avoids unnecessary flow of raw information from mobile end user to cloud server while processing and sharing the information.

Table 5 Results of Classification Performance of FCM Using Different Parameters

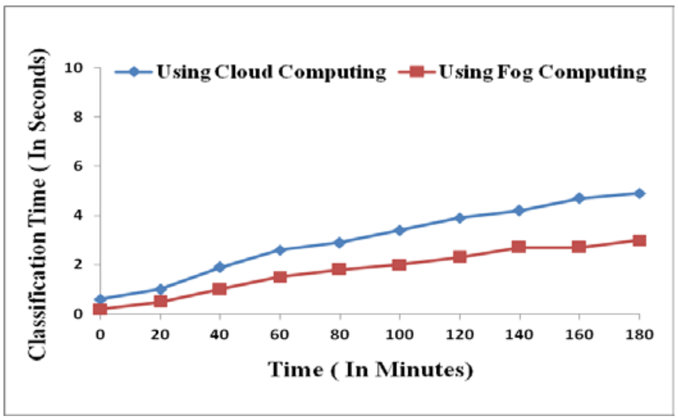
Statistical Parameters	**FCM m = 1.4 (in %)**	**FCM m = 1.6 (in %)**	**FCM m = 1.8 (in %)**	**FCM m = 2.0 (in %)**
Classification Accuracy	89.5	90.65	92.98	93.40
Sensitivity	86.7	87.3	88.4	90.45
Specificity	85.2	88.8	90.3	91.23
Precision	85.8	90.0	91.8	91.89
Recall	86.0	89.7	90.4	91.0
Mean Absolute Error	2.87	1.37	0.34	0.23
Root Mean Square Error	1.30	0.78	0.12	0.10
Relative Absolute Error	7.89	6.789	4.78	3.78



(a)



(b)



(c)

Figure 3 (a-c) Experimental Results: (a) Performance of Classification Accuracy of Different Algorithms (b) Execution Time of Different Algorithms (c) Total Execution Time of the FCM Classifier Using Fog Computing as Compared to Cloud Computing.

Efficiency of Alert Generation from Fog Layer

The efficiency of alert generation is primarily determined by how well CHV diagnosis works with fog computing to generate accurate and timely alerts. The validity of the alert generated based on the user's health status is investigated using the proposed system. The primary goal of statistically evaluating the alert generation component's efficiency is to confirm false positive alerts. These alerts are based on the total number of alerts and assess how long it takes to generate an alert and send information to the doctor and user. The difference in time between when an event occurs and when it is alerted to the user is the delay time. Fog-based alert generation and cloud-based alert generation for physicians are contrasted as a comparative model.

The results are shown in Figure 4, which shows the estimated delay time for cloud and fog-based computing. The findings demonstrate that when an abnormal or emergency situation arises, real-time notification from the fog system is far more effective than cloud-based notifications with minimal delay. For this purpose, a number of additional statistical parameters are also taken into account, including mean absolute error, root average square error, root relative squared error, coverage, sensitivity, specificity, and precision. Table 6 displays all of these findings. Given the low number of false positive alerts, statistical parameters show that the suggested system is very accurate and efficient. Furthermore, lower error rates improve the usefulness of the alert generation technique.

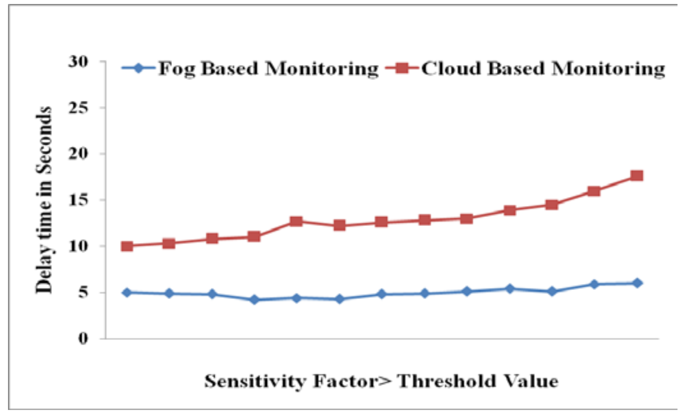


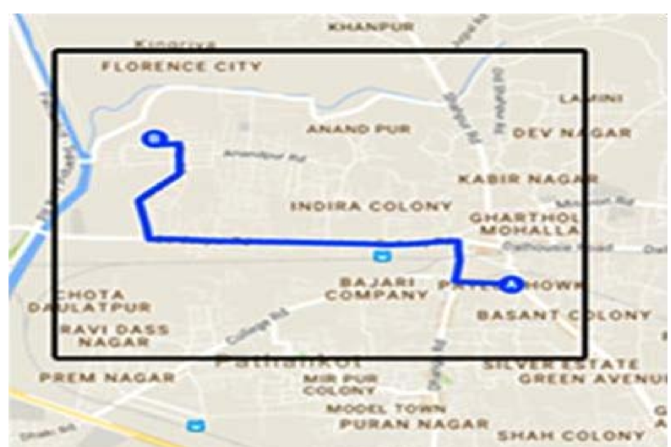
Figure 4 Efficiency of Delay Time

Table 6 Statistical Results of Alert Generation

Statistical Parameters	Values (in %)
Sensitivity	88.4
Specificity	94.5
Precision	91.4
Coverage	96.5
Mean Absolute Error	2.98
Root Average Square Error	2.50
Root Relative Square Error	34.4
Relative Absolute Error	7.68
False Positive Alerts	3.12

Evaluation of SNA Graph Based Risk Assessment

Data about infected users and their travel locations during CHV infection are generated over the Indian city of Pathankot in order to assess the SNA graph based risk assessment of infected and risk prone regions. In the specific Pathankot city block, two files in the.csv format with the travel itinerary information of five thousand users are mapped in the shape of a hexagon, as seen in Figures 5(a)



(a)

(b)

(c)

Figure 5 (a-c) Experimental Results: (a) GPS based Rerouting of User from Location A to Location B (b) Default Routing of User from Location A to Location B (c) Safe Route of the User based on Infected and Risk Prone Regions.

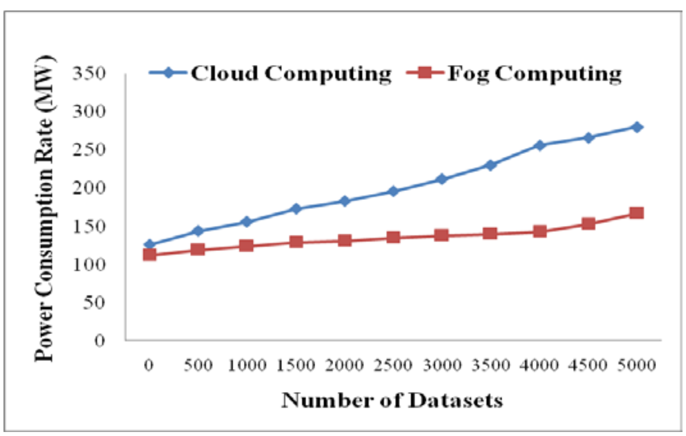


Figure 6 Comparative Analysis of Power Consumption Rate between Fog Computingand Cloud Computing

and 5 (b). Without using a routing algorithm, Figure 5(b) shows the user's route from location A to location B. Here, the user travels through areas that are both risky and infected, raising the possibility of contracting CHV infection. Alternatively, the user has used the proper routing to veer off onto the safer path.

Comparative Analysis of Power Consumption Rate

The comparison results are shown in Figure 6 which represents thecomparison of power consumption rate of both fog computing and cloud computing with respectto different datasets. The trend of graph shows that power consumption is more in case of cloud computing as compared to fog computing.

Conclusion

This paper reports fog based healthcare approaches that use classifiers to accurately diagnose the user's health category from CHV and promptly send diagnostic alerts to the user's mobile device from the fog layer. The utilization of sensitivity factors in relation to the timing of different events to assess the severity of health issues is the primary characteristic of this work. Emergency alerts are generated based on health severity in order to send event information to users' mobile devices via fog layer in a timely manner. Moreover, the state of the outbreak is depicted using analysis graphs. Analysis graphs are used to calculate a variety of metrics, including the likelihood that any given user will contract or spread the infection. Additionally, it produces timely warning alerts for non-infected individuals who are traveling or residing.

Conflict of Interest

Authors declare that there is no conflict of interest.

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