# IoT and cloud-based COVID-19 risk of infection prediction using hesitant intuitionistic fuzzy set

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**Abstract**

The outbreak of COVID-19 from Wuhan, China in 2019 has spread across the world, with more than 687 million confirmed coronavirus cases still increasing. Vaccines and medicines are one aspect of fighting the pandemic outbreak, but modern Information Technologies, web/ mobile-based technologies, blockchain, and Internet of Things (IoT) devices are being used to control the pandemic outbreak at an earlier/later stage. The IoT devices with sensors, and mobile apps/ websites having self-assessment tests can help in tracking COVID-19 infections. These people's tracking information and self-assessment tests are generating huge amounts of data. This white paper introduces an IoT and cloud-based architectural framework in the COVID-19 pandemic to predict infection risk based on citizens' self-assessments and storage of data in the cloud and the intelligent technique of hesitant Intuitionistic Fuzzy Set (IFS) has been used on the self-assessment dataset to predict the risk.

**Keywords** Pandemic COVID-19 · Cloud and IoT · IFS · Bluetooth · COVID-19 tracing mobile app/website

## 1 Introduction

A novel virus category called coronaviruses may affect persons as well as animals at large and can damage the respiratory, hepatic, lung, cardio, gastrointestinal, and neurologic systems. The respiratory disease may have some symptoms which include cold and fever. Many people may have mild sickness (Kumar et al. 2020). The list of such symptoms includes low fever to high fever, cold/ cough, and breathing issues. Such infection can be identified by a bio test named PCR (Polymerase Chain Reaction). At present, there are no specific medicines, treatments, and vaccinations available. The prevention of this virus is to use alcohol-based sanitizer and frequent washing hands and use masks and social distancing. These include the SARS-COV coronavirus. The other outbreaks were in SARS-CoV and MERS-CoV in 2003 and 2012 (Al-Qaness et al. 2020). World Health Organization (WHO)

came to know that many people are complaining related to respiratory illness when visiting the seafood market in Wuhan (WHO Organization, Novel coronavirus (2019)). In research, researchers found that COVID-19 may likely originated from bats (Lu et al. 2020; Mills et al. 2004). Researchers also found that COVID-19 spreads with close human contact and droplets of infected humans. Thus, a WHO advisory is issued for all countries to take intensified measures to control the COVID-19 identify infected persons and quickly isolate and quarantine (Heymann and Shindo 2020). The incubation duration for the infected person is decided to 14 days and in this period; it can infect others also (Cheng and Shan 2019). This virus impacted a lot of social life, the economy, and health across the world. In the last hundred years, such deadly virus-caused pandemics have been seen in 1918, 1957, and 1968 (Mills et al. 2004). The virus impacted cities a lot which contribute approximately 80% of the gross domestic product and 50% of worldwide people reside (World Bank Urban Development 2019). As a result of this, people living in cities have a high vulnerability to being infected. The enormous scale of the crisis and the impact it is having are naturally causing a lot of fear, uncertainty, and anxiety across the globe. Add social isolation, disrupted work and

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family routines, cabin fever, and economic instability, and, understandably, mental health is suffering. Rapid development, population growth, global travel, and the concept of smart cities contributed to the transmission of infection. On a large scale, it is impossible to trace an infected person. Thus, there is the probability of increased use of the latest technology such as blockchain, big data, smart mobiles, Bluetooth devices, etc. to stop the spreading of viruses. These smart technologies can be used to reduce the COVID-19 disease spread rate or other future pandemics. The technology-driven approach can be used for transmission under control using IoT short-range devices rather than a human-driven approach. Chinese government adopted a technology-driven approach and used sophisticated technology for surveillance during the first three months of the outbreak in Wuhan China (Kummitha 2020). After Wuhan, the outbreak of COVID-19 started in Western countries, and transmission of the virus was at full pace in the first three months. Following the China government's steps to control transmission, a lockdown across cities is imposed. Surveillance of infected persons with contact tracing, and COVID-19 symptoms detection using technology-driven methods are used to control transmission. In India, the very first detection of the COVID-19 outbreak was in January 2020. The Indian government has taken a lot of measures to control the transmission of the virus. The government started screening passengers from abroad, a lockdown was imposed, and airlines, metro, and railway services were suspended across the country. Aarogya Setu mobile application was launched by the Indian government in April 2020 to trace infected citizens. Self-assessment questions are available to assess the health condition of citizens. This mobile app works on Bluetooth technology to check the proximity of person to person. To curb the pandemic, short-range communication working on the internet can be used. IoT devices can not only be used for connecting sensing devices but also can act on data collected by devices and automate the process without human intervention (Chatterjee et al. 2018). The huge data collected from IoT devices and AI algorithms for analyzing data to better serve citizens is part of Smart Governance. For, cameras installed in public places can warn the citizens about a pandemic when cameras detect overcrowded public places. IoT-enabled services can be used in other places such as health, trade, culture, industry, etc. (Kankanhalli et al. 2019). Artificial techniques can be applied to quantitative and qualitative data. In the case of COVID-19 self-assessment test, a set of questions is available to assess the health and their responses are collected in linguistic/ vague form. For analyzing and decision-making, there is a need to apply some mathematical techniques. Thus, the concept of Intuitionistic Fuzzy Set (IFS) came into effect.

An intuitionistic fuzzy set concept was given by Atanassov in 1986. This theory is an extension of fuzzy set theory where the description of the problem is given in linguistic value which is too vague. It has been widely used in predicting various things such as logic programming, decision-making, etc. IFS has three functions in a fuzzy set named membership value, non-membership, and hesitance value. Hesitancy value played a very impressive role in predicting diseases. Sanchez's methodology has been used for medical diagnosis using the IFS theory. This paper has taken the self-assessment test questionnaire and answers of the Aarogya Setu Contact tracing app of the Indian government to predict the risk of infection of COVID-19 using IFS methodology.

The rest of the paper is organized as follows: Sect. 2 contains the literature review of related works.

## 2 Literature review and related work

Population growth and the concept of electronic governance started to give birth to the concept of a smart city (Lee and Lee 2014). In a smart city, it is expected that various information technology activities based on IoT devices will be collecting huge amounts of data, and AI, a machine learning algorithm can be applied to serve citizens. IoT devices are made of sensors, central processors, wearable items, software applications, actuators, Bluetooth, wi-fi, cell phones/ mobiles, etc. (Kankanhalli et al. 2019). The dedicated algorithm can be applied to know the pattern of data generated from IoT devices (Davenport and Ronanki 2018). Data collected from weather systems using IoT devices are being used for predicting weather changes (Kitchin 2014). Zambada, et al. (2015), proposed a school bus tracking system with the use of local systems and speed sensors devices, and IoT devices. The authors (Ballaa and Galb 2014) discussed short communication IoT devices. Noah et al. in 2020 (Peeri et al. 2020) discussed the Centers for Disease Control and Prevention (CDC, USA) website, and PubMed study, and found some clinical signs and symptoms, cure and identification, spreading way, safeguard methods, and threat factors for Middle East Respiratory Syndrome (MERS), Severe Acute Respiratory Syndrome (SARS) and new disease COVID-19. In China, AI-based contactless body temperature determination is installed at all metro stations for screening body temperature which can screen up to 15 patients every second up to a 3-m distance (Kummitha 2020). The related work areas are discussed in Table 1.

From a literature review, there is no framework available that could combine the whole cycle of citizen health data collection, storage, and analytics for smart health governance during any pandemic like COVID-19. IoT

**Table 1** Related Work

| Authors | Strength | Weakness |
| --- | --- | --- |
| Kitchin (2014) | Discussed real-time analysis of city-life big data collected from various sources | What big data analytics can help in urbanization, open, productive, competitive, and transparent cities? |
| Zambada et al. (2015) | School bus monitoring system with the use of localization and speed sensors-based IoT devices | Techniques of alerting IoT-based speed sensors alerting and localization are not discussed |
| Kummitha (2020) | Discussed AI-based contactless body temperature determination in China | Human drive questionnaire approach for determination of COVID-19 not discussed |
| Angelidou (2014) | Smart cities strategize their advantages/ disadvantages, and recommendations are discussed | IoT-based community information gathering missing |
| Axelsson and Granath (2018) | The city planning project, stakeholder, framework, and smart city governance were discussed | IoT-based energy and utilities management system for balancing energy usage and consuming devices |
| Gomez et al. (2016) | Framework for monitoring health and providing medical advice to patients with chronic disease | IoT-based medical wearable devices are missing |
| Mohammed et al. (2020) | Discussed the smart method of a thermal imaging system for finding the contaminated person amid the throng | Usage of IoT devices in monitoring the COVID-19 patients missing |
| Rajarajeswari and Dhanalakshmi (2013) | Intuitionistic Fuzzy soft matrix for medical diagnosis | Data collection and storage missing for further usage |
| Edward Samuel and Rajakumar (2017) | IFS with a new set for medical diagnosis | Data collection and storage missing for further usage |
| De et al. (2001) | Discussed the application of IFS in medical applications | Only medical diagnosis application examples are provided |
| Chopra et al. (2022) | Sustainable Development Goals (SDG) by the UN examined before and after COVID-19 | SDG index examined and compared |
| Sani et al. (2022) | COVID-19 Detection Using Chest X-Ray Images Based on Deep Learning | Chest X-ray-based COVID-19 detection |
| Tarhini et al. (2022) | Artificial Intelligence-Based Digital Transformation for Sustainable Societies during COVID-19 pandemic | The work is only related to digital transformation during COVID-19 |
| Proposed Work | An Intelligent IoT and cloud-based framework to predict COVID-19 and other diseases | IFS with hesitancy value has been used to predict the risk of any disease or COVID-19 |

devices/ human interventions like self-assessment questionnaire tests would generate data on their health and there is a need to store the data and analytics is also required to alert individuals about their health. The use of advanced technology like IoT sensors/ devices/wearable devices is part of sustainable smart cities development.

To understand the IoT-based smart city development, the rest of the paper is organized as follows: Sect. 3 gives an introduction to smart cities in the context of Indian Smart Cities.

## 3 Smart Indian cities

In 2014, the Indian government announced to building of 100 smart cities for modernization, rapid urbanization, and development of Indian cities as a response to global challenges of urbanization (Husar et al. 2017). The idea behind Smart is to use information and communication technology and develop a system that could think like the human brain with the use of Artificial Intelligence (AI). The concept of

PURA (Providing urban amenities in Rural Areas) is given by APJ Abdul Kalam with the objective of not moving the rural population into towns. PURA is related to providing three basic connectives – physical connectivity, electronic connectivity, and economic connectivity. The concept of a smart city deals with handling population growth, climate change, environmental changes, urban threats, weather warnings, crime, congestion, economic stagnation, smart drainage, smart buildings, smart education, etc. (Bauman and Lyon 2013). Scholars have discussed several models concerning smart cities, cyber cities (McNeill 2015), digital cities (Ishida 2000), and urban informatics (Boyer 1992). Varghese (2016) analyzed the smart city status in India and the issues such as power shortages and cuts, overpopulated areas, nonfunctional public transport, not ample water supply, no proper sewer system, cleanness of cities, health problems, etc. In India, various schools are using GPS-based bus tracking system that allows parents and school administrators to track the bus. The popularity of smartphones has drastically increased in India. Around 500 million users in India are using a smartphone. The

mobile application has become most popular for reaching citizens of India. During the time of the COVID-19 pandemic, the National Informatics Centre (NIC), Government of India developed the Aarogya Setu mobile application for contact tracking of Covid patients and people who came in close contact (Aarogya Setu app). This application traces contact based on Bluetooth technology and records information on mobile. This application also predicts the risk of infection based on some AI algorithms and self-assessment tests.

The next section discusses the IoT-based AI in smart cities and the use of IoT devices to fight against COVID-19.

### 3.1 IoT-based Artificial Intelligence (AI) in smart cities

IoT provides smart solutions with the interconnection of the physical world to the human world. In New York USA, IoT technologies are used for gathering details about the community (Angelidou 2014). Barcelona of Spain also used IoT-based systems to augment its usage of smart technologies (Kamel Boulos and Al-Shorbaji 2014). IoT-based AI can be used in field areas of Smart governance to enhance the lives of citizens of the country. Axelsson and Granath 2018 discussed the IoT-based energy and utilities management system for balancing energy usage and consuming devices. Gomez et al. (2016) proposed a framework for monitoring health and providing medical advice to patients with chronic diseases. Mohammed et al. (2020) discussed the smart method of a thermal imaging system for finding the contaminated person amid the throng.

### 3.2 IoT-based devices to fight COVID-19

IoT-based technology with machine learning, AI, and data science algorithms can be applied to detect COVID-19 potential patients and their close contact while they are infected. To control the pandemic, social distancing is the main term which means there should be some approx. 6 ft. distance between people. But in crowded workplaces, social distancing, LoRaWaN or Bluetooth technology can be used to alert people while social distancing is not maintained. These devices are wearable all the time while in public places or workplaces. We can also divide the whole working area into zones and there should be some alert mechanism when anyone is violating guidelines. There should also limit on the gathering in the work area and public areas. The audio-based warning should be available when maximum density is reached. IoT-based sanitization based on public gathering and time-bound should be there. Disinfection of assets should be in practice frequently. IoT-based device data collection, storage, and

analytics to fight COVID-19 of the data requires the framework to operate.

The rest of the paper is organized as follows: Sect. 4 proposes the IoT and cloud-based framework to fight pandemics like COVID-19.

## 4 Proposed model of IoT and cloud-based framework to fight COVID-19

As counting of corona-infected persons reached 687 million and limited health facilities, so Indian government decided to home quarantine/isolate those who have mild symptoms. However proper home monitoring is required to have IoT-based wearables attached to patients and these devices should be able to inform the designated care team regarding patients' health status from time to time. For COVID-19 infected patients, routine temperature measurement, oxygen level, room temperature, blood pressure, and sugar level determination devices should be attached and all information/ alerts should be sent when the patient reaches critical condition. Patients need to use wearable sensors that can measure Electrocardiography (ECG), highness of Temperature, Electromyography (EMG) muscle activity, breathing rate, sweating conditions, and glucose level in blood. By using such advanced devices with IoT capability, diseases named arrhythmia, sickness, abnormality in neuromuscular, blood flow, obesity, and sugar level can be detected. The combination of various measures can help to detect another disease. The sensors can be put in close contact with the skin in multiple body parts. They should be able to collect data and the IoT server should be able to collect data, analyze, and inform the doctors if the patient's condition is not as per the measurement. The electronic sphygmomanometer with Bluetooth has been used to keep continuous data such as SBP-Systolic Blood Pressure, DBP- Diastolic Blood Pressure, and Heart Rate. This system can detect any abnormality and inform the people accordingly.

By enabling the electronic sphygmomanometer to communicate via Bluetooth, an Android application was developed to record the data such as SBP-Systolic Blood Pressure, DBP—Diastolic Blood Pressure, and Heart Bit Rate. These applications made it easy to transmit the saved data using any cell phone device and this data is then recorded, and an abnormality is detected and informed to the people (Antonovici et al. 2014). The author proposed a synergic deep learning-based smart health COVID-19 diagnosis using chest X-ray. This model has mutual learning capability from one another (Shankar et al. 2021).

In this section, an IoT and cloud-based framework and flowchart of framework for COVID-19 patients has been
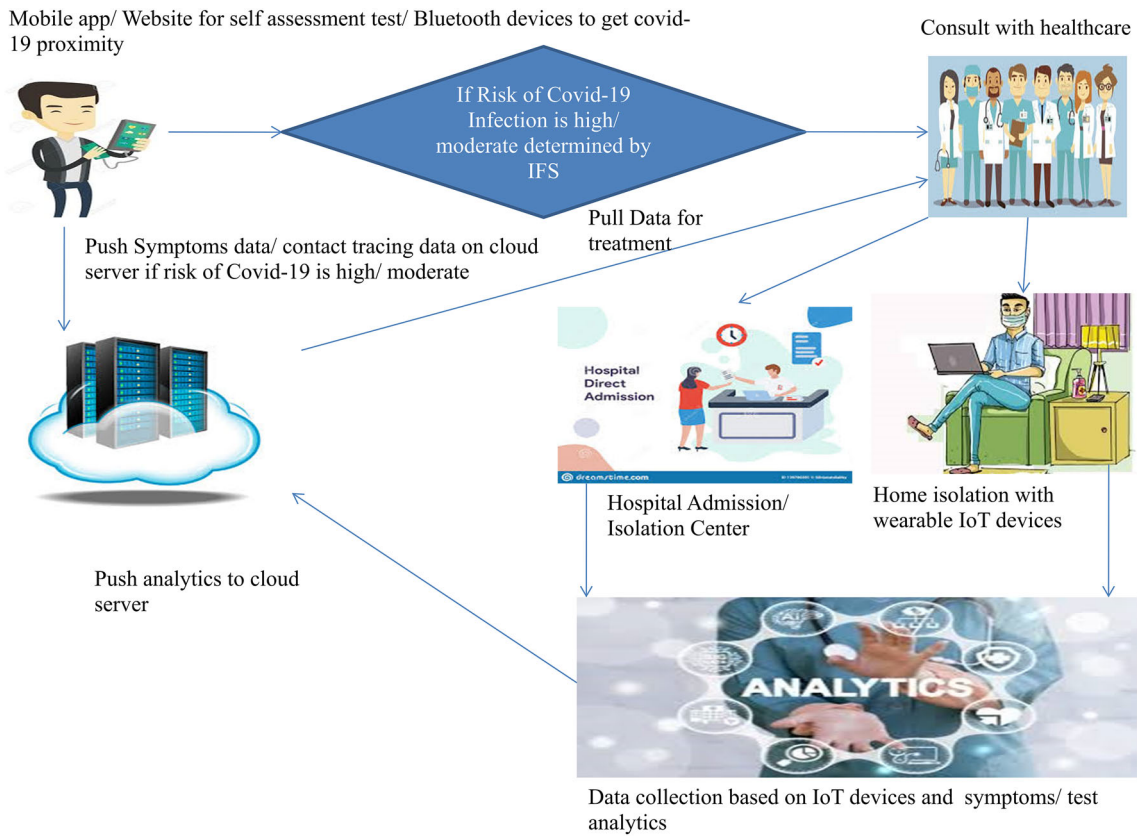
Mobile app/ Website for self assessment test/ Bluetooth devices to get covid-19 proximity

Consult with healthcare

If Risk of Covid-19 Infection is high/ moderate determined by IFS

Pull Data for treatment

Push Symptoms data/ contact tracing data on cloud server if risk of Covid-19 is high/ moderate

Hospital Direct Admission

Hospital Admission/ Isolation Center

Home isolation with wearable IoT devices

Push analytics to cloud server

ANALYTICS

Data collection based on IoT devices and symptoms/ test analytics

**Fig. 1** IoT and cloud-based framework for COVID-19

**Flowchart of framework**

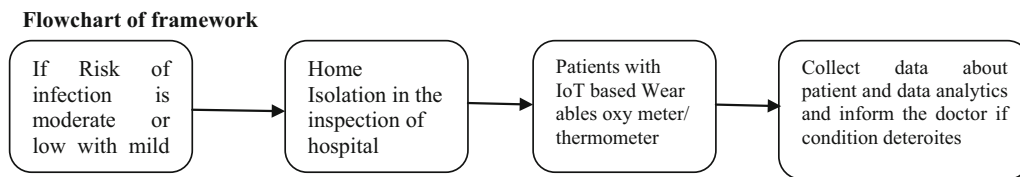| If Risk of infection is moderate or low with mild | → | Home Isolation in the inspection of hospital | → | Patients with IoT based Wear ables oxy meter/ thermometer | → | Collect data about patient and data analytics and inform the doctor if condition deteroites |

**Fig. 2** Flowchart of IoT and cloud-based framework for COVID-19

proposed in Figs. 1 and 2. The steps of the framework are as follows:

Step 1: firstly, any person performs self assessment test about the health and Bluetooth devices to get the COVID-19 proximity using COVID-19 tracing mobile app/ website.

Step 2: a self-assessment test data and risk of infection is predicted using a certain questionnaire.

Step 3: if the risk of infection is moderate or high then consult the health care system as well as data is pushed to the cloud server for further analytics.

Step 4: if any patient requires hospital admission/ isolation center or home isolation then IoT wearable devices could be attached to monitor the patient's condition.

Step 5: the data collected using IoT sensor wearable devices, IFS technique has been applied to detect the risk of any disease.

Step 6: in the same way, data is pushed to further analysis on the cloud storage server.

As COVID-19 tracing Mobile apps have self-assessment test features, there is a need to analyze the data using intelligent techniques named IFS.

## 4.1 Flowchart of framework

Various COVID-19 tracing Mobile apps based on Bluetooth Technology are being used in different countries.

(a)    Aarogya Setu App

This app is an initiative of the Indian government for contact tracing and prediction of the risk of infection. It is based on Bluetooth technology for contact tracing and records the timestamp and GPS of all contacts on mobile. If there is an infection in any contact, then the app predicts the risk of infection.

(b)  Tawakkalna (COVID-19 KSA)

This app was developed with the support of Saudi Arabia's Ministry of Health. It tracks the movement of people with color-based coding. The green color represents that person is allowed to travel, the yellow color is the offender and the red color is restricted to travel.

(c)  TraceTogether

This app was launched by the Singapore government to tackle the COVID-19 pandemic. It was developed to allow community-driven contact tracing to alert about the COVID-19 positive patients. It is being used by approximately 17% of the Singapore Population.

(d)  LetsBeatCOVID

This app was launched by MedShr, a London-based medical startup that allows users to assess their health by participating in the survey and getting a personalized report. This app also asks to link their relative details.

(e)  CovidWatch

This app was developed with the support of Stanford University. This is the first such type of app to trace people and their infection to alert accordingly when they are nearby of an infected person.

As COVID-19 tracing Mobile apps have a self-assessment test feature, the questions of self self-assessment of the Aarogya Setu COVID-19 tracing app are shown in Fig. 3. In question no. 3, Information is in vague form and the remaining information is in crisp form. There is a need to analyze the data using intelligent techniques named IFS.

The rest of the paper is organized as follows: Sect. 5 discusses the methodology of the IFS.

# 5 Methodology

In this section, basic definitions of IFS theory have been presented.

**Definition 5.1** Let's assume that there is a set S. An intuitionistic fuzzy set or IFS in S is an object in the form.

A = $\{x, \mu_A(x), \gamma_A(x) | x \in S\}$,

Where $\mu_A : S \rightarrow [0, 1]$ and $\gamma_A = S \rightarrow [0, 1]$ is used to describe the degree of membership and non-membership

respectively to the element $x \in S$ to set A, which is subset of E, for every $x \in S$.

$0 \leq \mu_A(x) + \gamma_A(x) \leq 1$ and $1 - ((\mu_A(x) + \gamma_A(x))$ represents hesitancy value which may part of either membership or non - membership value both.

**Definition 5.2** If A and B are two IFSs of the set E, then

$A \subset B$ if $\forall x \in E$, $[\mu_A(x) \leq \mu_B(x)$ and $v_A(x) \geq v_B(x)]$,
$A \supset B$ iff $B \supset A$,
$A = B$ if $\forall x \in E$, $[\mu_A(x) = \mu_B(x)$ and $v_A(x) = v_B(x)]$,
$\overline{A} = \{\langle x, v_A(x), \mu_A(x) \rangle | x \in E\}$,
$A \cap B = \{\langle x, \min(\mu_A(x), \mu_B(x)), \max(v_A(x), v_B(x)) \rangle | x \in E\}$,
$A \cup B = \{\langle x, \max(\mu_A(x), \mu_B(x)), \min(v_A(x), v_B(x)) \rangle | x \in E\}$.

Every fuzzy set has the form
$\{\langle x, \mu_A(x), \mu_{A^c}(x) \rangle | x \in E\}$.

**Definition 5.3** Let X and Y are two sets. An intuitionistic fuzzy relation (IFR) R from X to Y will be denoted by $R(X \rightarrow Y)$.

**Definition 5.4** If A is an IFS of X, the max min–max composition of the IFR $R(X \rightarrow Y)$ with A is an IFS B of Y denoted by $B = R \circ A$, and is defined by the membership function

$$\mu_{R \circ A}(y) = \bigvee_x [\mu_A(x) \wedge \mu_R(x, y)] \text{ And the non}$$
$$- \text{ membership function} \tag{1}$$

$$v_{R \circ A}(y) = \bigwedge_x [v_A(x) \vee \mu_R(x, y)] \quad \forall y \in Y \tag{2}$$

(where $\vee = \max$, $\wedge = \min$).

**Definition 5.5** Let $Q(X \rightarrow Y)$ and $Q(X \rightarrow Y)$ be two IFRs. The max–min-max composition $R \circ Q$ is the intuitionistic fuzzy relation from X to Z, defined by the membership function.

$$\mu_{R \circ Q}(x, z) = \bigvee_y [\mu_Q(x, y) \wedge \mu_R(y, z)] \quad \text{The membership}$$

function.

$$v_{R \circ Q}(x, z) = \bigwedge_y [v_Q(x, y) \wedge v_R(y, z)] \quad \forall (x, z) \in X \times Z \text{ and}$$

$\forall y \in Y$.

**Proposition 5.6** If R and S are two IFRs on $X \times Y$ and $Y \times Z$ respectively, then.

(i)  $(R^{-1})^{-1} = R$,
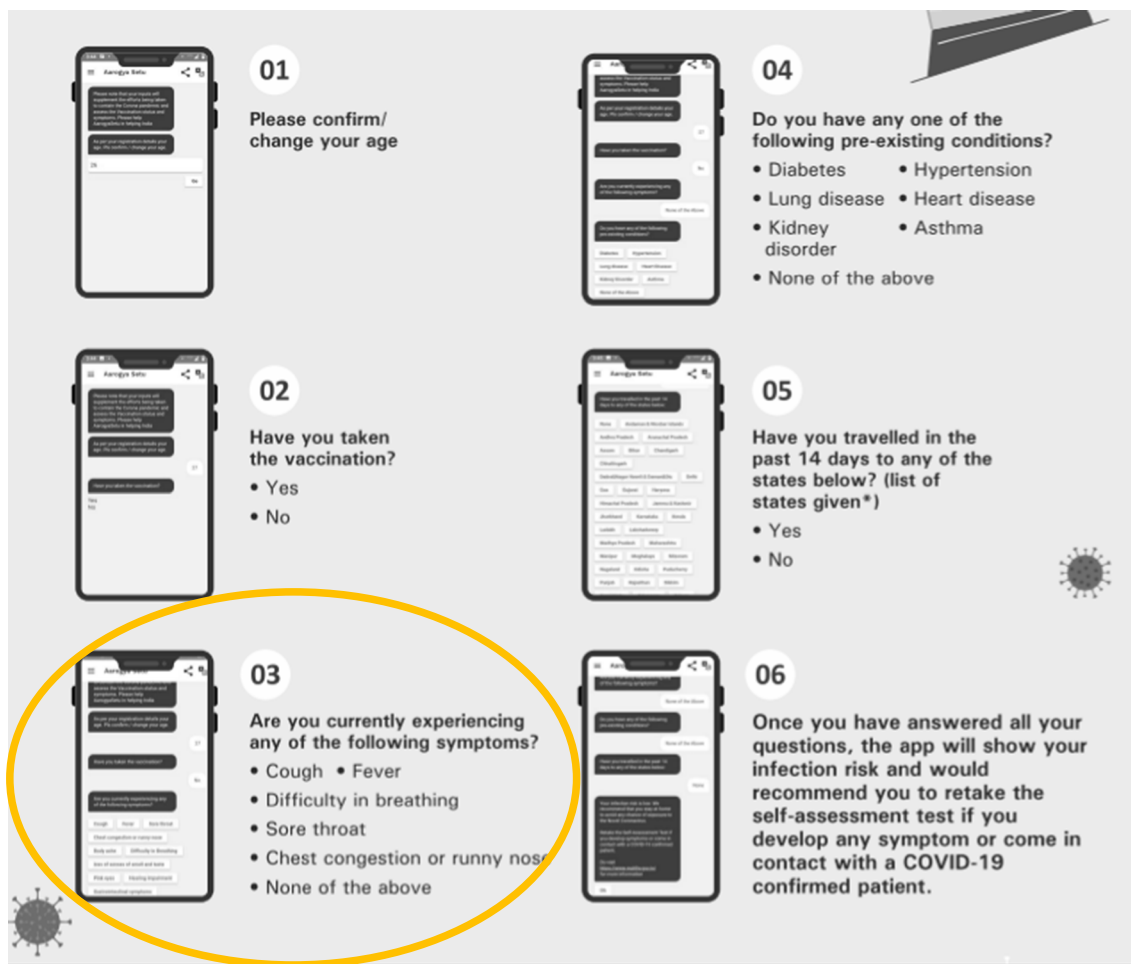(ii)  $(S \circ R)^{-1} = R^{-1} \circ S^{-1}$

**Fig. 3** Aarogya Setu COVID-19 tracing app questions

## 5.1 COVID-19 diagnosis

In this section, It has discussed the application of IFS in Sanchez's approach (Aarogya Setu app) to medical data. In the given data, suppose $S$ is the symptoms set, $D$ is the disease set, and $P$ is the patient's set.

Now, we define "Intuitionistic Medical Knowledge" as an Intuitionistic fuzzy relation (IFR) $R(S \rightarrow D)$ , which involves the degree of membership and degree of non-membership between symptoms and disease.

Now, it has been discussed the intuitionistic fuzzy medical disease. This method involves three important steps:

Step 1: Find out the symptoms.
Step 2: Based on IFR, we make medical knowledge.
Step 3: Based on IFR, find out the disease.

Let $A$ be an IFS of the $S$, and $R$ be an IFR from S to D. The max min–max composition (Biswas 1997) $B$ of IFS $A$ with the IFR $R(S \rightarrow D)$ denoted by $B = R \circ A$, signifies the condition of the patient in the form of the identified disease as an IFS $B$ of $D$ with the membership function given by

$$\mu_B(d) = \bigvee_{s \in S} [\mu_A(s) \wedge \mu_R(s,d)]$$  The non-membership function

$$v_B(d) = \bigwedge_{s \in S} [v_A(s) \vee v_R(s,d)]. \ \ \forall d \in D.$$

(here $\vee = $ max, $\wedge = $ min).

Patient $P$ is termed as an IFS A of S, and P has assigned disease in terms of IFS B of D, through an IFR R of "Intuitionistic Medical Knowledge" from S to D which is assumed by a physician who can translate his observation of intuitionism involved in the degree of association and non-association between symptoms and diseases.

Now let us consider generalizing the concept of a finite number of patients.

$p_i \in P$, i $= 1,2,3....$n represents the set of patients in a hospital. Let R be IFR $R(S \rightarrow D)$ and $Q(P \rightarrow S)$.

The composition $R$ and Q $(T = R \circ Q)$ describes the state of patients $p_i$ in terms of disease as an IFR from P to D given by the membership function

$$\mu_T(p_i, d) = \bigvee_{s \in S} \left[ \mu_Q(p_i, s) \wedge \mu_R(s, d) \right]$$

And the non-membership function given by

$$v_T(p_i, d) = \bigwedge_{s \in S} \left[ v_Q(p_i, s) \wedge v_R(s, d) \right] \forall p_i \in P \text{ and } d \in D.$$

For a given $R$ and $Q$ $(T = R \circ Q)$ can be computed. Using Q and T we compute the following:

$$\begin{array}{ll} (i) & S_R = \mu_R - v_R . \pi_R \\ & (ii) \quad (T = R \circ Q) \end{array} \tag{3}$$

The normalized Hamming distance for all symptoms of I the patients from kth diagnosis is given by:

$$\begin{aligned} (i) \quad l(s(p_i, d_k)) = \frac{1}{10} \sum_{j=1}^{5} & (|\mu_j(p_i) - \mu_j(d_k)| + |\lambda_j(p_i) - \lambda_j(d_k)| \\ & + |\pi_j(p_i) - \pi_j(d_k)|) \end{aligned} \tag{4}$$

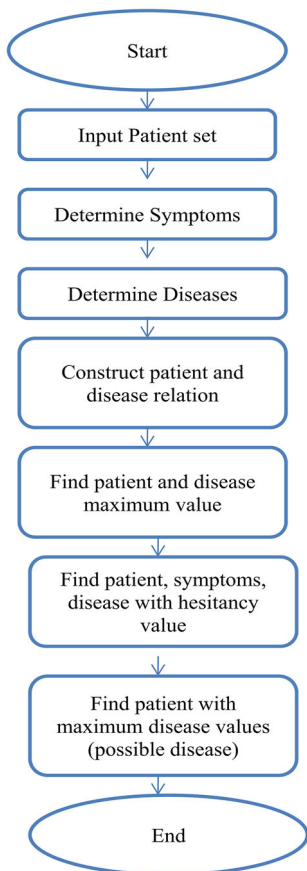The next Sect. 5.8 discusses the COVID-19 diagnosis flowchart.

## 5.2 COVID-19 diagnosis flowchart

The discussed steps are shown in the flowchart of Fig. 4. As per the flowchart, the following steps are as follows:

Step 1: Input the patient's sets, and determine symptoms and possible diseases.
Step 2: Construct patient and symptom relation.
Step 3: Construct symptom and disease relation.
Step 4: Find patient and disease value having hesitancy with maximum value.
Step 5: The maximum value is the predicted disease.

The rest of the paper is organized as follows: Sect. 6 provides the numerical simulation of COVID-19 diagnosis flowchart.

## 6 Numerical simulation

Let there be five patients with symptoms. The intuitionistic fuzzy relation R (P- > S) is shown in Table 2. Table 3 represents the IFR between symptoms and disease T (S- > D). The composition of Table 4 is based on applying equations in 1 and 2. Table 5 is made by using Eq. 3. Tables 6, 7 represents the symptoms and patients by three numbers: membership, non-membership, and hesitancy. Table 8 represents the possible diagnosis of patients by applying Eq. 4.

Table 8 with the maximum value in the row represents the diagnosis/ risk of infection or disease. Table 8 shows that patients P2 and P4 can be infected with COVID-19 while patient P1 may suffer from malaria or COVID-19 illness. While Table 5 predicts that P1 and P5 may suffer from COVID-19 disease. This is also represented by a chart diagram in Fig. 5. Section 7 evaluates the performance of the algorithm.

## 7 Performance evaluation

To evaluate the performance of the proposed model, the following method has been used. F-measure. F-measure is dependent upon a confusion matrix.

### 7.1 Confusion matrix

The confusion matrix is used to visualize the performance of the model. Each row in the matrix represents the predicted/ computed result and the column represents the actual instance. The resulting matrix consists of four values (Table 9).



**Fig. 4** Flowchart of COVID-19 diagnosis

**Table 2** Intuitionistic fuzzy relation R between patients and symptoms

| Patients/Symptoms | Temperature | Cough | Chronic disease | Smell/taste lost | Close Proximity of COVID-19 patient |
|---|---|---|---|---|---|
| P1 | (0.7, 0.2) | (0.6, 0.1) | (0.2, 0.7) | (0.3, 0.4) | (0.8, 0.1) |
| P2 | (0.1, 0.7) | (0.4, 0.5) | (0.1, 0.7) | (0.1, 0.7) | (0.2, 0.7) |
| P3 | (0.8, 0.1) | (0.7, 0.2) | (0.6, 0.3) | (0.2, 0.7) | (0.3, 0.6) |
| P4 | (0.7, 0.2) | (0.8, 0.1) | (0.3, 0.6) | (0.8, 0.1) | (0.1, 0.7) |
| P5 | (0.6, 0.1) | (0.5, 0.4) | (0.3, 0.6) | (0.6, 0.2) | (0.7, 0.2) |

**Table 3** Intuitionistic fuzzy relation R between symptoms and diseases

| Disease/Symptoms | Viral fever | Malaria | Dengue | Chikungunya | COVID-19 |
|---|---|---|---|---|---|
| Temperature | (0.4, 0.2) | (0.7, 0.1) | (0.2, 0.7) | (0.2, 0.4) | (0.2, 0.6) |
| Cough | (0.3, 0.5) | (0.1, 0.7) | (0.1, 0.7) | (0.6, 0.1) | (0.1, 0.7) |
| Chronic Disease | (0.2, 0.6) | (0.2, 0.6) | (0.2, 0.7) | (0.2, 0.7) | (0.2, 0.8) |
| Smell/ taste loss | (0.2, 0.7) | (0.2, 0.5) | (0.1, 0.8) | (0.3, 0.5) | (0.2, 0.8) |
| The close proximity of COVID-19 Patient | (0.1, 0.8) | (0.1, 0.8) | (0.2, 0.8) | (0.1, 0.7) | (0.8, 0.1) |

**Table 4** After applying Eqs. 1 and 2

| Disease/Symptoms | Viral fever | Malaria | Dengue | Chikungunya | COVID-19 |
|---|---|---|---|---|---|
| P1 | (0.4,0.2) | (0.7,0.2) | (0.2,0.7) | (0.6,0.1) | (0.8,0.1) |
| P2 | (0.3,0.5) | (0.1,0.7) | (0.2,0.7) | (0.4,0.5) | (0.2,0.7) |
| P3 | (0.4,0.2) | (0.7,0.1) | (0.2,0.7) | (0.6,0.2) | (0.3,0.6) |
| P4 | (0.4,0.2) | (0.7,0.2) | (0.2,0.7) | (0.6,0.1) | (0.2,0.6) |
| P5 | (0.4,0.2) | (0.6,0.1) | (0.2,0.7) | (0.5,0.4) | (0.7,0.2) |

**Table 5** After applying Eq. 3

| Patients/Diseases | Viral Fever | Malaria | Dengue | Chikungunya | COVID-19 |
|---|---|---|---|---|---|
| P1 | 0.32 | 0.68 | 0.57 | 0.57 | **0.79** |
| P2 | 0.2 | 0.04 | 0.35 | 0.35 | 0.13 |
| P3 | 0.32 | 0.68 | 0.56 | 0.56 | 0.24 |
| P4 | 0.32 | 0.68 | 0.57 | 0.57 | 0.08 |
| P5 | 0.32 | 0.57 | 0.46 | 0.46 | **0.68** |

**Table 6** Patients and symptoms with membership, non-membership, and hesitancy

| Patients/Symptoms | Temperature | Cough | Chronic disease | Smell/ taste lost | Close proximity of COVID-19 patient |
|---|---|---|---|---|---|
| P1 | (0.7, 0.2, 0.1) | (0.6, 0.1, 0.3) | (0.2, 0.7.0.1) | (0.3, 0.4, 0.3) | (0.8, 0.1, 0.1) |
| P2 | (0.1, 0.7, 0.2) | (0.4, 0.5, 0.1) | (0.1, 0.7, 0.2) | (0.1, 0.7, 0.2) | (0.2, 0.7, 0.1) |
| P3 | (0.8, 0.1, 0.1) | (0.7, 0.2, 0.1) | (0.6, 0.3, 0.1) | (0.2, 0.7, 0.1) | (0.3, 0.6, 0.1) |
| P4 | (0.7, 0.2, 0.1) | (0.8, 0.1, 0.1) | (0.3, 0.6, 0.1) | (0.8, 0.1, 0.1) | (0.1, 0.7, 0.2) |
| P5 | (0.6, 0.1, 0.3) | (0.5, 0.4, 0.1) | (0.3, 0.6, 0.1) | (0.4, 0.5, 0.1) | (0.7, 0.2, 0.1) |

**Table 7** Symptoms and diseases with membership, non-membership, and hesitancy

| Symptoms/Disease | Viral Fever | Malaria | Dengue | Chikungunya | COVID-19 |
|---|---|---|---|---|---|
| Temperature | (0.4, 0.2, 0.4) | (0.7, 0.1, 0.2) | (0.2, 0.7, 0.1) | (0.2, 0.4, 0.4) | (0.2, 0.6, 0.2) |
| Cough | (0.3, 0.5, 0.2) | (0.1, 0.7, 0.2) | (0.1, 0.7, 0.2) | (0.6, 0.1, 0.3) | (0.1, 0.7, 0.2) |
| Chronic Disease | (0.2, 0.6, 0.2) | (0.2, 0.6, 0.2) | (0.2, 0.7, 0.1) | (0.2, 0.7, 0.1) | (0.2, 0.8, 0.0) |
| Smell/ taste loss | (0.2, 0.7, 0.1) | (0.2, 0.5, 0.3) | (0.1, 0.8, 0.1) | (0.3, 0.5, 0.2) | (0.2, 0.8, 0.0) |
| Close proximity of COVID-19 Patient | (0.1, 0.8, 0.1) | (0.1, 0.8, 0.1) | (0.2, 0.8, 0.0) | (0.1, 0.7, 0.2) | (0.8, 0.1, 0.1) |

**Table 8** Possible diagnosis of patients by applying Eq. 4

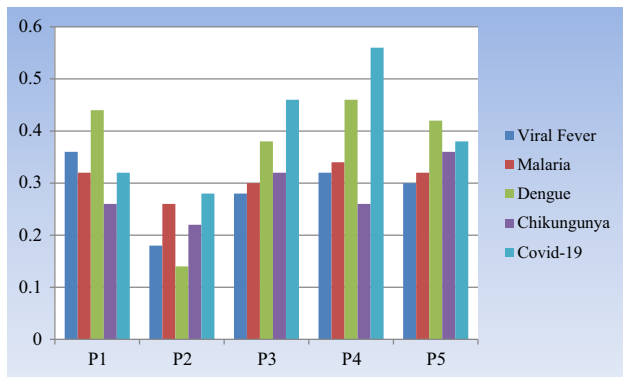| Patients/Diseases | Viral Fever | Malaria | Dengue | Chikungunya | COVID-19 |
|---|---|---|---|---|---|
| P1 | 0.36 | **0.32** | 0.44 | 0.26 | **0.32** |
| P2 | 0.18 | 0.26 | 0.14 | 0.22 | **0.28** |
| P3 | 0.28 | 0.3 | 0.38 | 0.32 | 0.46 |
| P4 | 0.32 | 0.34 | 0.46 | 0.26 | **0.56** |
| P5 | 0.3 | 0.32 | 0.42 | 0.36 | 0.38 |



**Fig. 5** Prediction of possible disease diagnosed in patients using IFS

(i) True Negative (TN): Predicted is negative which is true.

(ii) False Positive (FP): Predicted is positive which is false. It is also called a Type I error.

(iii) False Negative (FN): Predicted is negative which is false. It is also called a Type II error.

(iv) True Positive (TP): Predicted is positive which is true.

Precision can be seen as a measure of quality, and recall as a measure of quantity.

Precision represents the number of positive class predictions that belong to the positive class.

$$\text{Precision or positive predictive value} = TP/(TP + FP)$$

The recall is calculated based on the number of positive class predictions made out of all positive examples in the dataset.

$$\text{Sensitivity, recall, hit rate, or true positive rate} = TP/(TP + FN)$$

The F-score, also called the F1-score/ measure, is a measure of a model's accuracy on a dataset. It is used to evaluate binary classification systems, which classify examples into 'positive' or 'negative'.

$$\text{F1 measure} = (2 \times \text{precision} \times \text{recall})/(\text{precision} + \text{recall}).$$

## 7.2 Discussion

This model is tested with test data received from the internet source. The sample data consist of patient details with symptoms, COVID-19 details in text form. These text data are converted into the discussed model form and disease is predicted. The model is tested around 102 patient

**Table 9** Confusion Matrix

| Confusion matrix | Predicted | |
|---|---|---|
| | Negative (0) | Positive (1) |
| Actual | | |
| False (0) | True Negative (TN) | False Positive (FP) Type I Error |
| True (1) | False Negative (FN) Type II Error | True Positive (TP) |

**Table 10** Test Matrix

| Confusion Matrix (102) | | Predicted | |
|---|---|---|---|
| | | Negative (0) | Positive (1) |
| Actual | False (0) | TN – 8 | FP – 7 |
| | True (1) | FN – 13 | TP – 74 |

**Table 11** Performance matrix

| Sr. No. | Performance matrix | Data set |
|---|---|---|
| 1 | Positive predictive value | 0.91 |
| 2 | Recall | 0.85 |
| 3 | F1-Score | 1.034 |
| 4 | Accuracy | 0.80 |

data and the model is run. The test matrix based on the test is shown below (Table 10).

Precision or positive predictive value (P)
$= TP/(TP + FP) = 74/(74 + 7) = 0.91$

Sensitivity, Recall or hit rate $(R) = TP/(TP + FN)$
$= 74/(74 + 13) = 0.85$

F1 measure $= 2PR/P + R = 1.034$

Overall Accuracy $= (TP + TN)/(TP + FP + FN + TN)$
$= (74 + 8)/(74 + 7 + 13 + 8)$
$= 0.80$

Thus, the overall accuracy of the methodology is 80%. The result is also analyzed in terms of F1 measure. The performance matrix of proposed model is shown in Table 11.

Table 12 shows the comparison of results with the proposed framework approach with IFS and the hesitancy-based IFS approach. The result shows that IFS with hesitancy value predicts the possibility of COVID-19 in patients P1, P2, and P4 which is higher than IFS-based.

For testing of this model, same methodology has been applied for the prediction of 53 covid patients and the model predicted for 39 patients. The model is also compared with the statistical technique of regression (Li et al. 2023). Regression technique is used to predict a numerical value based on some input variable. In two predictions, Mean Absolute Error (MAE) as (18.5), Mean Squared Error (MSE) (344.5), and Root Mean Squared Error (RMSE) (18.56) have been calculated. The calculated RMSE is much closer MAE. RMSE indicates average model prediction error. So this model has RMSE is 18.56

much closer to 20%. It indicates that model can have accuracy above 80%.

## 7.3 Implication and significance of cloud and IoT-based framework

IoT offers many advantages for proactively predicting health issues and streamlining and improving healthcare delivery to detect, take care of, and supervise patients both in and out of hospitals. Government leaders and policy-makers around the world are implementing policies to leverage technology to deliver health services, particularly in response to the COVID-19 pandemic. It is increasingly important to understand how established and emerging IoT technologies can help health systems provide safe and effective care. It's about outlining how care can be impacted and disrupted. IoT-based healthcare poses barriers to market adoption, trust and acceptance, privacy and security, interoperability, standardization, and compensation, data storage in the cloud, control and ownership by healthcare professionals and patients. The successful implementation of IoT in healthcare today depends on political support, cybersecurity-focused policies, careful strategic planning, and transparent policies within healthcare organizations. IoT-based healthcare has great potential to increase the efficiency of healthcare systems and improve human health.

## 7.4 Challenges and barriers of the proposed model

Policy support to adopt e-health, prevention of cyber attacks on personal information as all the communication is wireless, data storage, control, ownership, standardization of processes, and remuneration for technology-assisted health are the challenges to implementing the IoT and cloud-based e-health framework.

## 7.5 Comparison to mitigate pandemic: traditional and IoT cloud-based framework

Traditionally, there is a need to curtail the interactions between infected and uninfected humans; e.g., patient isolation, quarantine, social distancing practices, and school closures. After that Reduce the infectiousness of symptomatic patients using antiviral and antibiotic treatment and infection control practices. Parallelly, Reduces the susceptibility of uninfected individuals using vaccines. In IoT and Cloud-based methodology, IoT devices, and contact tracing mobile apps would help to spread of pandemic. IoT wearable health devices would help in monitoring the patient's condition 24 × 7.

Section 8 concludes the proposed work.

**Table 12** Comparison table

| Patients | IFS-based disease prediction | IFS with hesitancy-based prediction |
|---|---|---|
| P1 | COVID-19 | COVID-19 |
| P2 | – | COVID-19 |
| P3 | – | – |
| P4 | – | COVID-19 |
| P5 | COVID-19 | – |

## 8 Conclusion

In this paper, IoT and cloud-based framework have been proposed that ensures IoT sensor-based data collection/storage on the cloud system and self-assessment test using COVID-19 website/mobile app for prediction of risk of infection in the pandemic like COVID-19 and other diseases. The IFS technique with hesitancy value has been applied to self-assessment reports provided by people. In IFS, the hesitancy value has been considered in patients, symptoms table, and symptoms, disease table, and found that finding the distance for all diseases concerning all symptoms with hesitancy is a more efficient approach than finding the disease without the hesitancy value. The final table gives more accurate results by predicting the additional disease in patients. The proposed model also alerts people with any diseases other than COVID-19. The MATLAB Intuitionistic Fuzzy (IF) Logic Toolbox helps to plot the standard membership and non-membership functions and implement the discussed methodology.

**Data availability** Enquiries about data availability should be directed to the authors.

## Declarations

**Conflict of interest** No.

**Ethical approval** I have tried to maintain high standards of personal conduct, practicing honesty in all our professional relationships and endeavors. We are truthful in our actions and words.

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