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A model for the effective COVID-19 identification in uncertainty environment using primary symptoms and CT scans

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Abstract

The rapid spread of the COVID-19 virus around the world poses a real threat to public safety. Some COVID-19 symptoms are similar to other viral chest diseases, which makes it challenging to develop models for effective detection of COVID-19 infection. This article advocates a model to differentiate between COVID-19 and other four viral chest diseases under uncertainty environment using the viruses primary symptoms and CT scans. The proposed model is based on a plithogenic set, which provides higher accurate evaluation results in an uncertain environment. The proposed model employs the best-worst method (BWM) and the technique in order of preference by similarity to ideal solution (TOPSIS). Besides, this study discusses how smart Internet of Things technology can assist medical staff in monitoring the spread of COVID-19. Experimental evaluation of the proposed model was conducted on five different chest diseases. Evaluation results demonstrate that the proposed model effectiveness in detecting the COVID-19 in all five cases achieving detection accuracy of up to 98%.

Keywords

COVID-19, viral chest diseases, symptoms, CT imaging, smart spaces, Internet of Things, Artificial Intelligence, Plithogenic, BWM, TOPSIS

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Introduction

Coronaviruses COVID-19 is considered a catastrophic global healthcare problem that involves respiratory, hepatic, gastrointestinal and neurological complications. Like common viral diseases, fighting the spread of the novel COVID-19 virus is a complicated mission and requires coordinated efforts by public healthcare authorities. COVID-19 was caused by SARS-CoV-2 virus. At the time of writing this paper, countries, where the outbreak has exceeded China, are USA, Italy and Spain. Countries like South Korea has been proven that early diagnosis is one of the most effective factors in controlling the disease and preventing its spread.

A large number of infections and the high speed of spread of COVID-19 around the world confirms that the virus is transmitted through carriers or between people, which poses a serious challenge to control its spread.[1,2,3] Therefore, various comprehensive preventive measures such as social distancing have to be taken worldwide to reduce the spread of infection. However, the ultimate measure to end the coronavirus pandemic is the creation of an effective vaccine. Experts and governments recognise that a vaccine may not be ready before 2 years, and this is not an inevitability. Therefore, an effective and immediate prevention mechanism must be adopted until a vaccine is developed.

The novel Coronavirus has an incubation period that begins from the first date of contact with the source of the virus and the date when symptoms appear on the virus carrier. The general symptoms of COVID-19 are fever, cough, nausea and shortness of breath.[4] Most viral chest diseases, for example, as H1N1, H5N1 and influenza, have the same symptoms as COVID-19 which may lead to the wrong diagnosis. The most common tools for the diagnosis of COVID-19 is the polymerase chain reaction (PCR), assay or a chest CT scan. The PCR method detects viral nucleic acids directly, but the chest CT scan determines volumes of infection in a segment, one side or both sides of the lung.[5]

In this article, we start by reviewing the role of various smart spaces enabling technologies in the efforts to compact the COVID-19 pandemic. Then, we propose an IoT-based model to outline the data flow between various smart spaces entities and demonstrate the potential in tracking, tracing, monitoring, imposing, controlling and even developing a vaccine for COVID-19. Then, we study the symptoms of the COVID-19 and the CT scan results to assist doctors inaccurate diagnosis of the disease by comparison with the other four viral chest diseases, namely, H1N1, H5N1, SARS and Hantavirus. This study formulates the evaluation of the symptoms and the CT imaging results as a multi-criteria decision-making (MCDM) problem. The criteria are the symptoms and the CT imaging results, and the alternatives are the viral chest diseases including COVID-19. The research considers the MCDM-driven evaluation under an uncertainty environment to achieve a more accurate evaluation. The proposed diagnosis model employs the best-worst method (BWM) technique in order of preference by similarity to ideal solution (TOPSIS) under a plithogenic environment.

The contribution of this work is four-folds. First, it aims to show the value of studying all aspects of the COVID-19 under uncertainty conditions. Second, an integrated IoT-based model for monitoring COVID-19 patients is presented. Third, we provide a model to evaluate the symptoms of the most viral chest diseases and the CT imaging results using the BWM. Third, we apply the proposed evaluation model to assess the five viral chest diseases based on a plithogenic set. Fourth, we combine the BWM with TOPSIS to attain a reliable framework that applies under uncertainty environment.

The rest of the paper is organised as follows: A literature review on COVID-19 impact and detection methods is presented in Section 2. Section 3 represents the preliminaries of COVID-19 and other relevant viral chest diseases. Section 4 proposes an IoT model for monitoring of

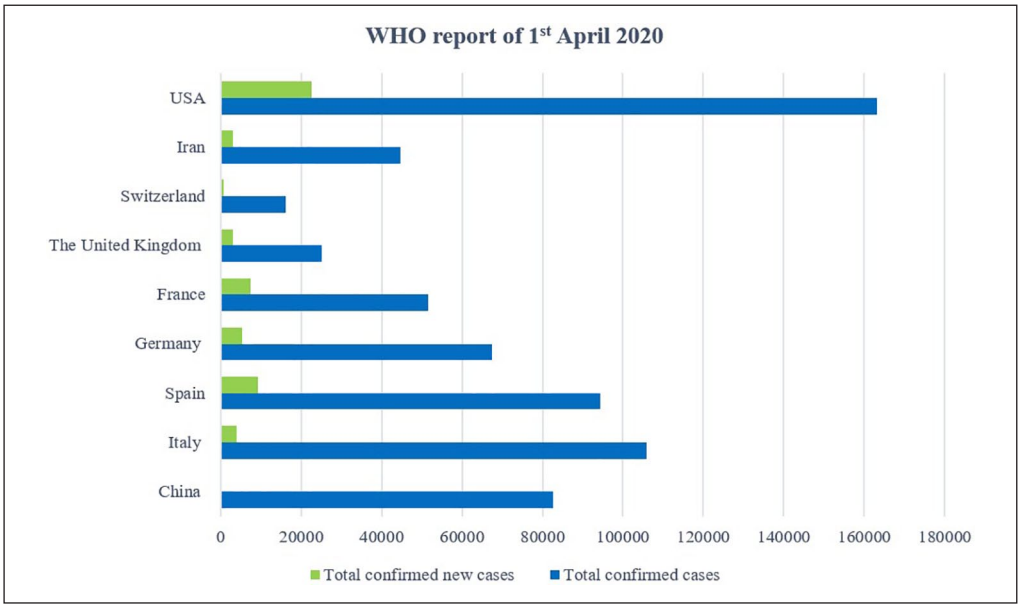


Figure 1. Confirmed cases of COVID in April 2020.[10,11]

COVID-19 patients. Section 5 gives the definitions and methods that constitute the proposed diagnosis model. In Section 6, the application of the proposed model to evaluate the symptoms and the CT imaging results of viral chest diseases are presented. Section 7 presents new directions that may help in studying the outbreak of COVID-19. Section 8 concludes the article and gives future work avenues.

Literature review

At the end of December 2019, a group of pneumonia cases were registered in Wuhan city in China for unspecified reasons. In the first week of January 2020, researchers confirmed the presence of a novel coronavirus that causes pneumonia which was named SARS-CoV-2.[6] This virus was confirmed and classified by real-time reverse transcription-polymerase chain reaction (RT-PCR).[7] On 11 February 2020, the World Health Organisation (WHO) declared COVID-19 a pandemic. The main symptoms that appear on most patients are fever (98%), cough (76%), shortness of breath (55%), fatigue (44%), sputum production (28%), headache (8%), haemoptysis (5%) and diarrhoea (3%).[8] Figure 1 shows the spread of COVID-19 around the world.[9]

A turning point for this epidemic would be the development of a vaccine. However, WHO estimates that this could take 18 months.[6] Until this time, anti-viral and anti-inflammatory treatments have been used to treat the symptoms of the virus. Thus, preventing the spread of the virus remains the first line of defence until a vaccine is developed. Concurrently, effective infection methods tools remain critical in the treatment and control of COVID-19 infections.

In the last few months, thousands of studies on COVID-19 diagnosis, treatment, control and impact appeared in the literature. Devaux et al. studied the possible mechanisms of chloroquine interference with COVID-19.[12] While Zhang et al. investigated whether some Chinese medical herbs can fight COVID-19 infection.[13] Phan et al. explored methods for the detection, clinical diagnosis and features of COVID-19.[14] Lupia et al. summarised the clinical aspects

of COVID-19 with suggestions for patients who may need antibiotic treatment.[15] Shen et al. summarised the currently available detection methods for COVID-19 to assist researchers in developing better tools for the detection of the infection.[11] Kooraki et al. studied radiology can support epidemiologists with the diagnosis of COVID-19.[10] Bonilla-Aldana et al. gathered information about COVID-19 using an Internet-based reporting system and proposed an improvement to the ProMED system to improve its efficiency during the outbreak.[16] From an economic perspective, McKibbin and Fernando examined the impacts of COVID-19 on macroeconomic outcomes in different scenarios.[17] Anderson et al. studied the impact of government strategies in fighting the COVID-19 pandemic.[18]

In the literature, MCDM methods have proven effective in many healthcare data-focused applications. Recently, Stevic et al. applied the MARCOS method in the evaluation of sustainable supplier selection in the healthcare industry.[19] Bhalaji et al. assessed the risk factors facing the healthcare product development process under a fuzzy environment.[20] Fei et al. evaluated the hospital service factors under uncertainty as an MCDM problem using BWM based on belief function theory (BFT).[21] In this work, we advance the literature with a new COVID-19 diagnosis model that employs BWM technique in order of preference by similarity to ideal solution (TOPSIS) under a plithogenic environment. We combine the BWM with TOPSIS to attain a reliable framework that applies under uncertainty environment.

Smart spaces enabling technologies for COVID-19 pandemic

Smart technologies are playing a vital role in the fight against COVID-19 such as predicting the disease spread patterns, the chance of infection, the opportunity of recovery, track and trace, amongst other uses. This section review some of the key smart spaces enabling technologies and how they are being used in the current pandemic.

- Artificial Intelligence (AI): AI is used for analysing and mining big data to build models to perceive, illustrate and estimate various COVID-19 patterns. It is also used in the development of vaccines and drugs. In many countries, AI is driving robots that perform sterilisation and disinfection operations, and are used in the manufacturing processes of medical equipment needed in the healthcare sector.
- IoT: IoT, specifically wearable and personal, devices are being used for collecting valuable data such as body temperature and geographical location of individuals. Amongst the many applications of IoT in the fight against COVID-19 is on drones to monitor quarantine operations as well as track and trace of people who may have contracted COVID-19.
- Big data mining: The information held in the huge volumes of data collected by medical personal, researchers, IoT devices, mobile networks or even crowed sourced can help decision-makers take the right actions at the right time to control the pandemic.
- Virtual reality (VR): VR proved to be a very useful tool for remote cooperation, training and communication without the need for real contact or travel.
- Cloud computing: It allows connecting and sharing of computer system resources such as processing power, storage resources, databases, networks and others through the Internet. This technology helps increase resource efficiency and reduce operating costs. Cloud computing helped solve many problems caused by the quarantine that was imposed to limit the spread of the virus. Applications have been introduced that help people continue their digital lives naturally such as Zoom video, Slack, Netflix through services such as Amazon Web Services, Microsoft Azure and Google Cloud.

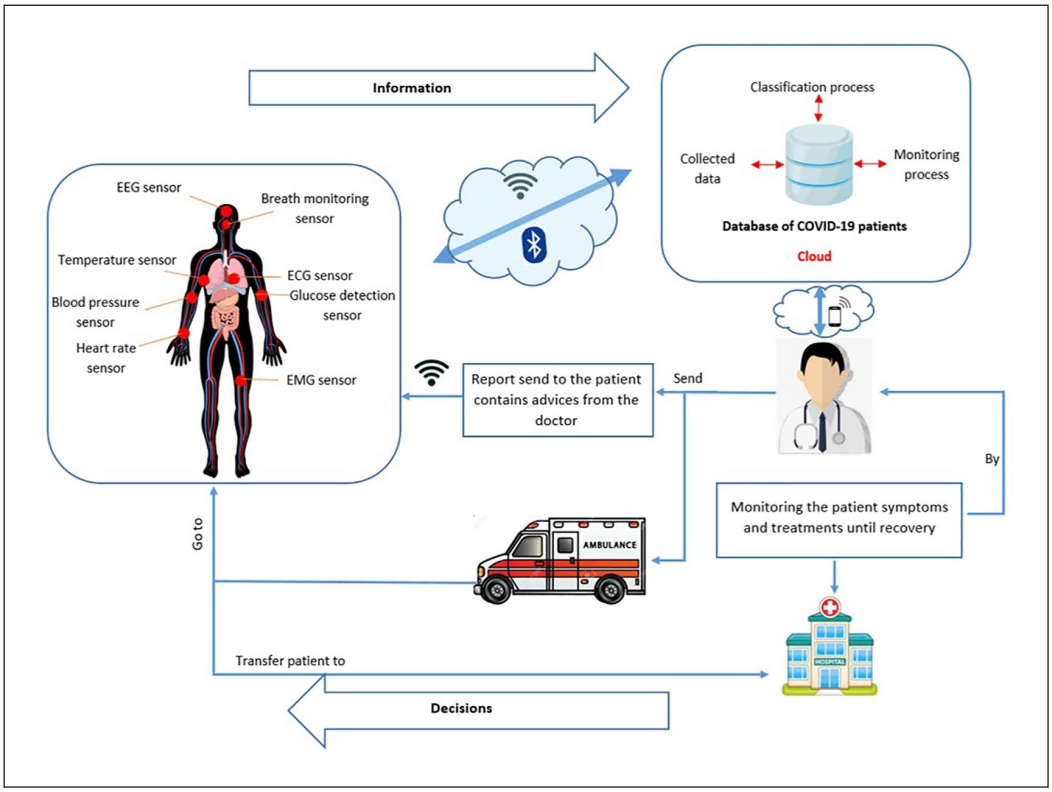


Figure 2. An IoT-based model for COVID-19 monitoring and control.

- Autonomous robots: Autonomous robots are AI-enabled robots used to collect information about the surrounding environment without assistance. They are being used on both the air and ground to monitor quarantine measures, social distancing and
- 3D scanning: This type of scanning is often used to perform human body imaging in the medical field, where it collects data on the shape and appearance of the body. It helps in the fight to compact COVID-19 through the thoracic chest scanning. It is also a valuable tool for identifying and quantifying COVID-19 viruses.

In the following, we illustrate an IoT-enabled model for detecting and monitoring COVID-19 patients using several body sensors. This model illustrates the contribution of smart technologies to effectively compact the COVID-19 pandemic. Information about the patient's health is collected through various body sensors. As shown in Figure 2, body sensors monitor the patient's health condition, including temperature, blood pressure, heart rate, respiratory monitoring, glucose detection, etc. This data is relayed through a gateway to a cloud platform where it can be processed and analysed. The databases contain AI-enabled expert systems that can classify the patient's condition. If a patient is diagnosed as being infected with or suspected to be infected with the virus, one of the following procedures can be taken: (1) The doctor determines based on the severity of the symptoms experienced by the patient whether the patient needs to be tested, transferred to a hospital or simply being monitored closely at home; (2) If the patient is diagnosed as unstable and needs intensive care, a report will be sent to the patient and his local

healthcare centre/hospital and an ambulance will be dispatched to transfer the patient to the hospital with free space to provide the needed care.

The system stores all the results of medical examinations and CT images that were made for the patient in the cloud databases for the doctors to follow the development of the patient's treatment. The remote monitoring, pooling or resources, data analysis and intelligent decision making has been determined as a key to successful utilisation of resources.

Proposed COVID-19 identification method preliminaries

A Model for the Effective COVID-19 Identification in Uncertainty Environment Using Primary Symptoms and CT Scans

In this section, we give the details of the various constituents of the proposed model for effectively identifying COVID-19 in uncertainty environment using primary disease symptoms and CT scans.

Plithogenic set

Ever since Florentin Smarandache introduced the theory of neutrosophic in 1998, it has been extensively applied in healthcare research. For instance,[22] proposed an IoT-based framework for cancer diagnosis based on the neutrosophic set and[23] proposed a medical image denoising method based on the neutrosophic set.[23] Plithogenic is a generalisation of crisp, fuzzy, intuitionistic fuzzy and neutrosophic set introduced by Smarandache.[22] A plithogenic set *(P, A, V, d, c)* is a set that comprises elements characterised by attributes' value $V = \{v_1, v_2, \ldots, v_n\}$, for $n \geqslant 1$, each attribute value has an appurtenance degree concerning some given criteria. The set attributes denoted as $A = \{\alpha_1, \alpha_2, \ldots, \alpha_m\}$, $m \geqslant 1$. The main contribution of the plithogenic set is to have more accurate aggregation operators which can be applied by the contradiction degree function *c(v, D)* that describes the relationship between attribute values and the dominant. Appurtenance degree function of the element x concerning set of given criteria is noted as *d(x,v)*.[24]

The attribute value contradiction degree function used in the plithogenic set operators are Intersection (AND), Union (OR), Implication (=>), Equivalence (⇔).

Definition 1. Let $\tilde{a} = (a1, a2, a3)$ and $\tilde{b} = (b1, b2, b3)$ be two plithogenic sets. The plithogenic intersection is given as:

$$\begin{aligned}&\left(\left(a_{i1}, a_{i2}, a_{i3}\right), 1 \leq i \leq n\right) \wedge \mathrm{p}\left(\left(b_{i1}, b_{i2}, b_{i3}\right), 1 \leq i \leq n\right)\\ &= \left(\left(a_{i1} \wedge_F b_{i1}, \frac{1}{2}\left(a_{i2} \wedge_F b_{i2}\right) + \frac{1}{2}\left(a_{i2} \vee_F b_{i2}\right), a_{i2} \vee_F b_{i3}\right)\right), 1 \leq i \leq n.\end{aligned} \tag{1}$$

The plithogenic union is given as:

$$\begin{aligned}&\left(\left(a_{i1}, a_{i2}, a_{i3}\right), 1 \leq i \leq n\right) \vee \mathrm{p}\left(\left(b_{i1}, b_{i2}, b_{i3}\right), 1 \leq i \leq n\right)\\ &= \left(\left(a_{i1} \vee_F b_{i1}, \frac{1}{2}\left(a_{i2} \wedge_F b_{i2}\right) + \frac{1}{2}\left(a_{i2} \vee_F b_{i2}\right), a_{i2} \wedge_F b_{i3}\right)\right), 1 \leq i \leq n.\end{aligned} \tag{2}$$

where

$$a_{i1} \wedge \mathrm{p}\, b_{i1} = \left[1 - c\left(v_D, v_1\right)\right].t_{norm}\left(v_D, v_1\right) + c\left(v_D, v_1\right).t_{conorm}\left(v_D, v_1\right) \tag{3}$$

$$a_{i1} \vee \mathrm{p}b_{i1} = \left[1 - c\left(v_D, v_1\right)\right].t_{conorm}\left(v_D, v_1\right) + c\left(v_D, v_1\right).t_{norm}\left(v_D, v_1\right) \tag{4}$$

where, $t_{norm} = \wedge_F b = ab$, $t_{conorm}\ a \vee_F b = a + b - ab$

Best-worst method

BWM is a simple vector-based method that requires fewer pairwise comparison than the analytical hierarchy process (AHP). BWM requires $2n-3$ comparisons, whereas AHP requires $n\ (n-1)/2$ comparisons.[25] BWM provides more consistent comparisons than AHP, hence, it provides more reliable results.[26] It compares the best criterion and the worst criterion with the rest of the problem criteria.[27] The steps of the BWM are as follows:

1. Define the set of decision criteria $C = \{c_1, c_2, \ldots, c_n\}$.
2. According to decision-maker preferences, the Best C_B and Worst C_W criterion are determined.
3. Construct the best-to-other vector $C_B = \{c_{B1}, c_{B2}, \ldots c_{Bn}\}$, where c is the preference of criteria n compared by the Best criterion B. In this step, decision-makers determine their judgement, using a number from 1 to 9 (where 1 is equally significant and 9 is extremely significant).
4. Construct the others-to-worst vector $C_w = \{c_{w1}, c_{w2}, \ldots c_{wn}\}$, where c_{wn} is the preference of criteria n compared by the Worst criterion W.
5. Use the BWM model to compute the optimal weights of the criteria w_n:

$$\begin{aligned} &\min \max \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_W} - a_{jW} \right| \right\} \\ &\text{s.t.} \\ &\sum_j w_j = 1 \\ &w_j \geq 0, \text{for all j} \end{aligned} \tag{5}$$

The equivalent model is:

$$\begin{aligned} &\text{Min } \varepsilon \\ &\text{s.t.} \\ &\left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \varepsilon, \text{ for all j} \\ &\left| \frac{w_j}{w_w} - a_{jW} \right| \leq \varepsilon, \text{ for all j} \\ &\sum_j w_j = 1 \\ &w_j \geq 0, \text{ for all j} \end{aligned} \tag{6}$$

TOPSIS

TOPSIS is a popular MCDM technique that aims to find the least and most distance between negative and positive ideal solution.[28] It chooses the alternative that has the shortest distance from a positive ideal solution and farthest from the negative ideal solution. The steps of TOPSIS operation are as follows:

1. Build the evaluation matrix $\tilde{D}$, where i is the alternative and j is the criteria, using equation 7.

$$\tilde{D} = \left[a_{ij} \right]_{m \times n} = \begin{bmatrix} a_{11} & a_{12} & \ldots & a_{1n} \\ a_{21} & a_{22} & \ldots & a_{21} \\ \ldots & \ldots & \ldots & \ldots \\ a_{m1} & a_{m2} & \ldots & a_{mn} \end{bmatrix}_{m \times n} \tag{7}$$

2. Normalise the evaluation matrix using equations 8 and 9.

$$\tilde{N} = \left[x_{ij} \right]_{m \times n} = \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1n} \\ x_{21} & x_{22} & \ldots & x_{21} \\ \ldots & \ldots & \ldots & \ldots \\ x_{m1} & x_{m2} & \ldots & x_{mn} \end{bmatrix}_{m \times n} \tag{8}$$

$$\text{where} \quad (x_{ij})_{m \times n} = \Big/ \left(\sqrt{\sum_{i=1}^{m} x_{ij}^2} \right) \tag{9}$$

3. Calculate the weighted normalised evaluation matrix using equation 10.

$$V = (v_{ij})_{m \times n} = w_j \times x_{ij} \tag{10}$$

where w_j is the priority of each criterion.

4. Determine the positive ideal solution and negative ideal solution using equations 11–14:

$$A^{+} = \left\{ v_1^{+}, v_2^{+}, \ldots, v_n^{+} \right\} \tag{11}$$

$$v^{+} = \{ (max_i \, v_{ij} | j \in J_b), (min_i \, v_{ij} | J \in J_{nb}) | \in \left[1 \ldots m \right] \}. \tag{12}$$

$$A^{-} = \left\{ v_1^{-}, v_2^{-}, \ldots, v_n^{-} \right\} \tag{13}$$

$$v^{-} = \{(min_i v_{ij} | j \in J_b), (max_i v_{ij} | J \in J_{nb}) | \in [1 \ldots m]\}. \tag{14}$$

where J_b is a set of beneficial criteria, and J_{nb} is a set of non-beneficial criteria

5. Calculate the distance of each alternative from PIS and NIS using equations 15 and 16.

$$d_i^{+} = \sqrt{\sum_{j=1}^{m} (V_i - V_j^{+})^2} \tag{15}$$

$$d_i^{-} = \sqrt{\sum_{j=1}^{m} (V_i - V_j^{-})^2} \tag{16}$$

6. Calculate the closeness coefficient CC_i for each alternative by using equation 17.

$$CC_i = \frac{d_i^{-}}{d_i^{+} - d_i^{-}} \tag{17}$$

A BWM- and TOPSIS-based method for COVID-19 identification

In this section, we present the details of an integrated MCDM method which is based on the plithogenic set to improve the accuracy of the evaluation process. This method integrates the features of the plithogenic set with BWM and TOPSIS. In this method, the plithogenic set provides accurate aggregation results while considering uncertainty, BWM evaluates the optimal weights of the criteria and TOPSIS determines the ranking of the optimal alternatives by measuring their distance from the positive and negative ideal solutions. Figure 3 is a conceptual illustration of the proposed methods. The steps of this method are:

1. Define a set of criteria $C = \{c_1, c_2, \ldots, c_n\}$, and alternatives $A = \{a_1, a_2, \ldots, a_m\}$ to build a MCDM problem. Determine a group of experts who will cooperate in evaluating the problem $DM = \{d_1, d_2, \ldots, d_k\}$.
2. Determine the weight of the criteria using BWM. The steps of the BWM are presented in Section 4.3.
3. Rank the alternatives using the TOPIS method.
   a) Each decision-maker *k* builds the evaluation matrix using the triangular neutrosophic evaluation scale (see Table 1).
   b) Aggregate the *k* decision matrices into a single decision matrix of all decision-makers' evaluations using plithogenic aggregation using equations (10–12).
   c) For simplification purposes, de-neutrosophication the aggregated decision matrix into crisp values using Eq. 18.

$$\mathrm{S}(\mathrm{a}) = \frac{1}{8}(a_1 + b_1 + c_1) \times (2 + \alpha - \theta - \beta) \tag{18}$$

4. Calculate the normalised and weighted normalised decision matrices according to Eq. 16, 17, and 18.

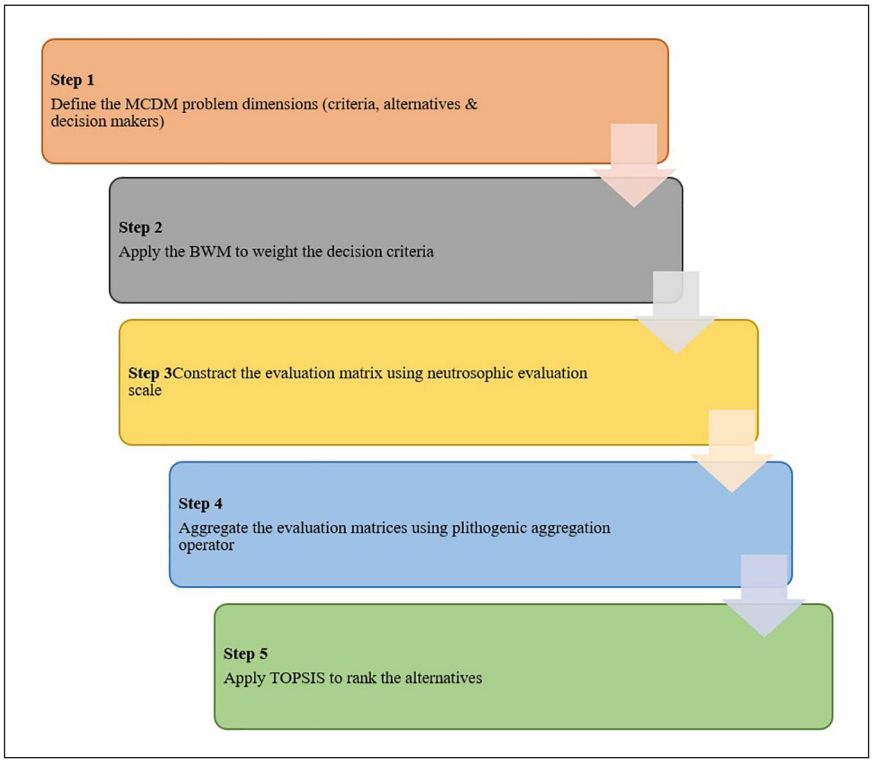


Figure 3. Steps of the proposed framework.

Table 1. Triangular neutrosophic evaluation scale.

Scale explanation	Neutrosophic triangular scale
Minimum occurrence (MO)	((0.10, 0.25,0.3),0.1,0.3,0.1)
Low occurrence (LO)	((0.2,0.3,0.50),0.6,0.2,0.3)
Partially occurrence (PO)	((0.45,0.3,0.50),0.6,0.1,0.2)
Equal occurrence (EO)	(0.5,0.5,0.50),0.9,0.1,0.1)
Strong occurrence (SO)	((0.7,0.75,0.80),0.9,0.2,0.2)
Very strongly occurrence (VSO)	((0.85,0.8,0.95),0.8,0.1,0.2)
Absolutely occurrence (AO)	((0.95,0.90,0.95),0.9,0.10,0.10)

5. Calculate the distance and the closeness coefficient using equations 11–15, and rank the alternatives according to the closeness coefficient.

Application of the proposed method

The symptoms of COVID-19 appear differently from one patient to another making accurate diagnosis a challenging task. However, like other viral chest diseases, COVID-19 has a set of common symptoms that appear on patients. Consequently, doctors face a serious challenge in the diagnosis

Table 2. Viral chest disease, symptoms, and CT imaging result.

Viral chest disease	Symptoms	CT imaging result
H1N1 COVID-19 H5N1 Hantavirus SARS	Chills Nasal congestion Headache Cough Sore throat Sputum production Fatigue Shortness of breath Fever	Non-appearance of Both Ground-Glass Opacities and Consolidation (Normal CT) The occurrence of Ground-Glass Opacities The occurrence of Ground-Glass Opacities with or without Consolidation The occurrence of Ground-Glass Opacities with Consolidation without effusion The occurrence of Ground-Glass Opacities with Consolidation effusion

Table 3. Best-to-others vector.

Best to others	Chills	Nasal congestion	Headache	Cough	Sore throat	Sputum production	Fatigue	Shortness of breath	Fever
Cough	5	7	4	1	3	8	6	9	2

of suspect cases before performing the PCR, that is, to take a preliminary decision on whether to perform further procedures. This adds to the doctor a sense of uncertainty in the diagnosis of this disease. Hence, this study attempts to assist doctors inaccurate diagnosis of COVID-19 through assessing patient's symptoms and the CT imaging result to differentiate them from four other common viral chest diseases under the uncertainty environment. Table 2 shows the main symptoms and the CT image results that will be used in distinguishing of COVID-19 against H1N1, H5N1, Hantavirus and SARS.

In the following, we detail the application of the proposed integrated method to evaluate the symptoms and the CT imaging result of differentiating between five viral chest disease including COVID-19. The first step of this method is measuring the priority of symptoms to each other and also to the results of the patient's CT image. To do so, the problem dimension must be specified first. The criteria in this application will be the common symptoms of viral chest diseases. The alternatives will be the five viral chest diseases. And the decision-makers in this problem are the specialists and doctors. In this application, we selected three doctors are specialised in this field to assist in these evaluations.

To calculate the weights of the symptoms, we determine cough as the best criterion and shortness of breath to be the worst. Best-to-others vector and others-to-worst vector are determined as specified in Tables 3 and 4 respectively. In many studies,[2,3] it has been proven that cough and high fever are the first symptoms to appear on a COVID-19 patient. Using the BWM model described in Table 5, we found that the weight of cough $= 0.3133$ and the weight of fever $= 0.1920$ as the highest two weights; hence, they are considered carefully. BWM evaluates the CT imaging result, where the best result will be the occurrence of Ground-Glass Opacities (GGO), while the worst is the occurrence of GGO with Consolidation Effusion. The result of the BWM model for evaluating the weight of each CT image is shown in Table 6. Using the neutrosophic evaluation scale shown in Table 1, each doctor constructs his own opinion about the evaluation of the five diseases according to the set of symptoms, as shown in Table 7. Then, the three doctors' evaluation matrices are aggregated using plithogenic aggregation operator based on equidistant contradiction degrees as

Table 4. Others-to-worst vector.

Others to the worst	Shortness of breath
Chills	4
Nasal congestion	3
Headache	6
Cough	9
Sore throat	7
Sputum production	2
Fatigue	5
Shortness of breath	1
Fever	8

Table 5. Weights of the symptoms using BWM.

Weights	Chills	Nasal congestion	Headache	Cough	Sore throat	Sputum production	Fatigue	Shortness of breath	Fever
	0.07681	0.0549	0.09601	0.3133	0.1280	0.0480	0.0640	0.02695	0.1920

Table 6. Weights of the CT results using BWM.

Weights	CT1	CT2	CT3	CT4	CT5
	0.04861	0.42361	0.13889	0.2778	0.1111

Table 7. Evaluation matrix of three doctors according to the observed symptoms.

Doctor 1	Chills	Nasal congestion	Headache	Cough	Sore throat	Sputum production	Fatigue	Shortness of breath	Fever
H1N1	EO	EO	SO	AO	SO	SO	VSO	VSO	VSO
COVID-19	EO	SO	SO	AO	VSO	PO	SO	LO	AO
H5N1	SO	LO	EO	VSO	VSO	LO	SO	SO	AO
Hanta Virus	VSO	LO	SO	VSO	EO	SO	EO	SO	AO
SARS	VSO	LO	VSO	SO	LO	LO	VSO	SO	AO
Doctor 2	Chills	Nasal congestion	Headache	Cough	Sore throat	Sputum production	Fatigue	Shortness of breath	Fever
H1N1	PO	SO	VSO	AO	SO	SO	SO	VSO	AO
COVID-19	SO	SO	VSO	VSO	VSO	EO	SO	LO	VSO
H5N1	SO	MO	EO	SO	SO	LO	VSO	SO	AO
Hanta Virus	SO	LO	SO	SO	PO	SO	EO	SO	VSO
SARS	VSO	LO	VSO	SO	LO	LO	VSO	SO	AO
Doctor 3	Chills	Nasal congestion	Headache	Cough	Sore throat	Sputum production	Fatigue	Shortness of breath	Fever
H1N1	SO	EO	VSO	AO	SO	SO	VSO	VSO	AO
COVID-19	EO	SO	SO	AO	VSO	PO	SO	LO	AO
H5N1	VSO	LO	PO	VSO	VSO	MO	SO	VSO	VSO
Hanta Virus	VSO	LO	VSO	VSO	EO	SO	EO	VSO	AO
SARS	VSO	LO	AO	SO	LO	LO	AO	SO	AO

Table 8. Aggregated evaluation matrix according to the known common symptoms.

Contradiction degree	0	0.11		0.89
Three doctors	Chills	Nasal congestion	. . .	Fever
H1N1	((0.16,0.58,0.95), 0.83,0.15,0.13)	((0.26,0.56,0.87), 0.9,0.13,0.1)	. . .	((0.99,0.88,0.88), 0.88,0.1,0.13)
COVID-19	((0.18,0.65,0.95), 0.9,0.13,0.1)	((0.43,0.75,0.96), 0.9,0.2,0.1)	. . .	((0.99,0.88,0.88), 0.88,0.1,0.13)
. . .	. . .	. . .	. . .	. . .
SARS	((0.61,0.8,0.1), 0.8,0.1,0.2)	((0.04,0.3,0.79), 0.6,0.2,0.3)		((0.99,0.9,0.88), 0.9,0.1,0.1)

Table 9. Crisp values of the aggregated evaluation matrix.

	Chills	Nasal congestion	Headache	Cough	Sore throat	Sputum production	Fatigue	Shortness of breath	Fever
H1N1	0.536	0.564	0.763	0.943	0.728	0.734	0.800	0.827	0.910
COVID-19	0.564	0.694	0.729	0.903	0.808	0.394	0.736	0.247	0.910
H5N1	0.698	0.266	0.431	0.778	0.789	0.258	0.760	0.774	0.881
Hanta Virus	0.724	0.298	0.742	0.778	0.467	0.734	0.506	0.774	0.910
SARS	0.754	0.298	0.854	0.720	0.267	0.258	0.884	0.736	0.936

Table 10. Normalised evaluation matrix.

	Chills	Nasal congestion	Headache	Cough	Sore throat	Sputum production	Fatigue	Shortness of breath	Fever
H1N1	0.233	0.245	0.332	0.410	0.316	0.319	0.348	0.359	0.395
COVID-19	0.269	0.332	0.348	0.431	0.386	0.188	0.351	0.118	0.434
H5N1	0.349	0.133	0.216	0.389	0.395	0.129	0.380	0.388	0.441
Hanta Virus	0.353	0.145	0.362	0.379	0.228	0.358	0.247	0.378	0.444
SARS	0.366	0.145	0.415	0.349	0.130	0.125	0.429	0.357	0.455

shown in Table 8. This is followed by de-neutrosophication of the aggregated evaluation matrix using equation 18. Table 9 shows the crisp evaluation matrix.

Table 10 shows the normalised evaluation matrix. Using equation 10, the weighted normalised evaluation matrix is calculated in Table 11. The weight in this step is calculated using the BWM model. The ranking of the five viral chest diseases according to the symptoms using the TOPSIS method is given in Table 12. The results of TOPSIS show that the patient with most of these symptoms is diagnosed with COVID-19 where CC = 0.985748, while SARS at the end of ranking with CC = 0.126606. The five viral chest diseases are ranked as follows: COVID-19 > H1N1 > H5N1 > Hantavirus > SARS (see Figure 4).

One of these research objectives is to apply the proposed method to evaluate the five virus chest diseases according to the common symptoms firstly and then using the CT imaging result. Table 13 shows the three doctors evaluation of the type of diseases according to the CT imaging. The

Table 11. Weighted normalised evaluation matrix.

	Chills	Nasal congestion	Headache	Cough	Sore throat	Sputum production	Fatigue	Shortness of breath	Fever
H1N1	0.018	0.013	0.032	0.128	0.040	0.015	0.022	0.010	0.076
COVID-19	0.021	0.018	0.033	0.135	0.049	0.009	0.022	0.003	0.083
H5N1	0.027	0.007	0.021	0.122	0.051	0.006	0.024	0.010	0.085
Hanta Virus	0.027	0.008	0.035	0.119	0.029	0.017	0.016	0.010	0.085
SARS	0.028	0.008	0.040	0.109	0.017	0.006	0.027	0.010	0.087

Table 12. Ranking of the five diseased according to the observed symptoms.

Alternatives	d^*	d^-	CC_i	Rank
H1N1	0.000000248	0.000001590	0.864822	2
COVID-19	0.000000066	0.000004548	0.985748	1
H5N1	0.000000633	0.000002533	0.800117	3
Hanta Virus	0.000000997	0.000000616	0.382053	4
SARS	0.000004170	0.000000605	0.126606	5

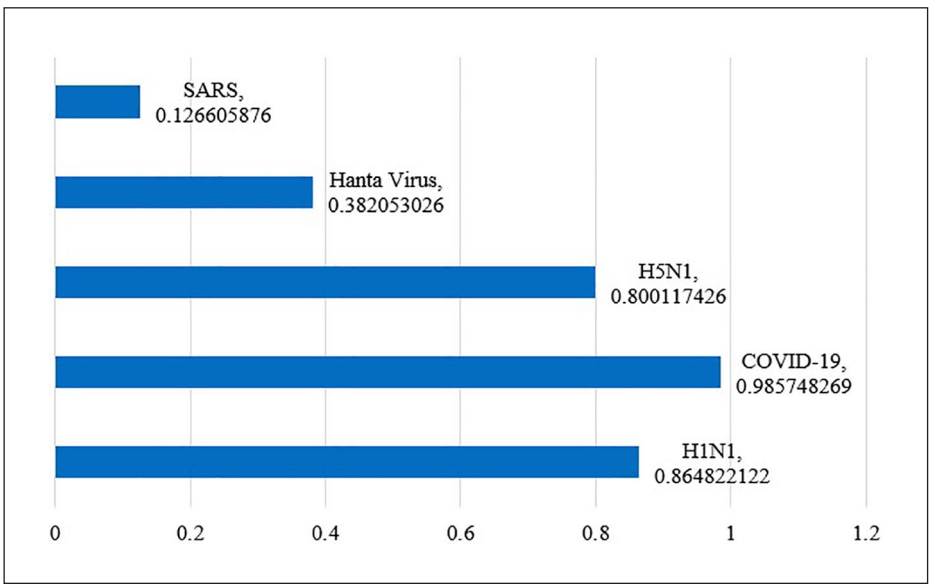


Figure 4. TOPSIS result according to the symptoms.

aggregation of the three doctors' evaluation is shown in Table 14. While the weighted normalised matrix is shown in Table 15. Finally, the evaluation of the five viral chest diseases using TOPSIS is shown in Table 16. The results of TOPSIS show that the patient with this CT imaging of CC = 0.8876 is mostly will be diagnosed COVID-19 positive, while Hantavirus came last with CC = 0.1692. The studied five viral chest diseases are ranked as follows: COVID-19 > SARS > H1N1 > H5N1 > Hantavirus (see Figure 5).

Table 13. Evaluation matrix of three doctors according to the CT imaging.

Doctor 1	CT1	CT2	CT3	CT4	CT5
H1N1	PI	VSI	EI	EI	SI
COVID-19	SI	AI	VSI	VSI	WI
H5N1	PI	VSI	EI	PI	SI
Hanta Virus	SI	SI	EI	EI	VSI
SARS	EI	SI	EI	VSI	VSI
Doctor 2	CT1	CT2	CT3	CT4	CT5
H1N1	EI	VSI	EI	EI	VSI
COVID-19	SI	AI	VSI	AI	PI
H5N1	PI	VSI	SI	PI	SI
Hanta Virus	SI	VSI	EI	EI	VSI
SARS	EI	SI	EI	SI	VSI
Doctor 3	CT1	CT2	CT3	CT4	CT5
H1N1	WI	VSI	EI	EI	VSI
COVID-19	SI	AI	VSI	VSI	WI
H5N1	WI	VSI	EI	PI	SI
Hanta Virus	VSI	SI	EI	EI	VSI
SARS	EI	SI	WI	VSI	VSI

Table 14. Aggregated evaluation matrix of diseases according to the CT imaging.

Contradiction degree	0	0.2		0.8
Three Doctors	CT1	CT2	. . .	CT5
H1N1	((0.05,0.35,0.88), 0.68,0.15,0.23)	((0.72,0.8,0.99), 0.8,0.1,0.2)	. . .	((0.94,0.79,0.81), 0.83,0.13,0.18)
COVID-19	((0.34,0.75,0.99), 0.9,0.2,0.1)	((0.9,0.9,0.99), 0.9,0.1,0.1)	. . .	((0.48,0.3,0.28), 0.6,0.18,0.28)
. . .	. . .	. . .	. . .	. . .
SARS	((0.13,0.5,0.88), 0.9,0.1,0.1)	((0.5,0.75,0.93), 0.9,0.2,0.1)		((0.95,0.8,0.9), 0.8,0.1,0.2)

Table 15. Weighted normalised matrix according to the CT imaging.

	CT1	CT2	CT3	CT4	CT5
H1N1	0.0129	0.2406	0.0510	0.1021	0.0645
COVID-19	0.0197	0.2383	0.0669	0.1412	0.0188
H5N1	0.0124	0.2533	0.0599	0.0763	0.0624
Hanta Virus	0.0228	0.2070	0.0473	0.0945	0.0618
SARS	0.0165	0.2008	0.0351	0.1489	0.0617

Table 16. Ranking of the five types of infections according to the CT imaging.

Alternatives	d^*	d^-	CC_i	Rank
H1N1	0.00000729	0.00002110	0.743112	3
COVID-19	0.00000567	0.00004478	0.887558	1
H5N1	0.00002950	0.00002785	0.485576	4
Hanta Virus	0.00003017	0.00000614	0.169179	5
SARS	0.00001456	0.00005085	0.777472	2

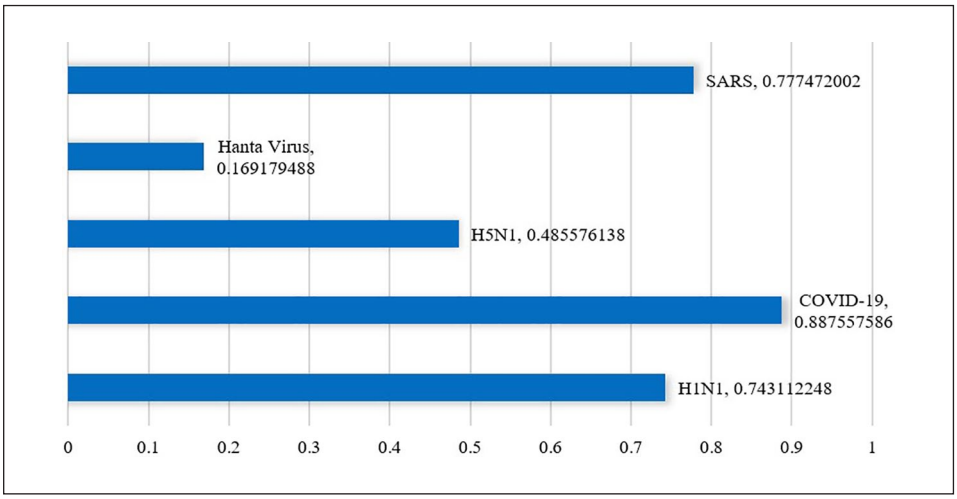


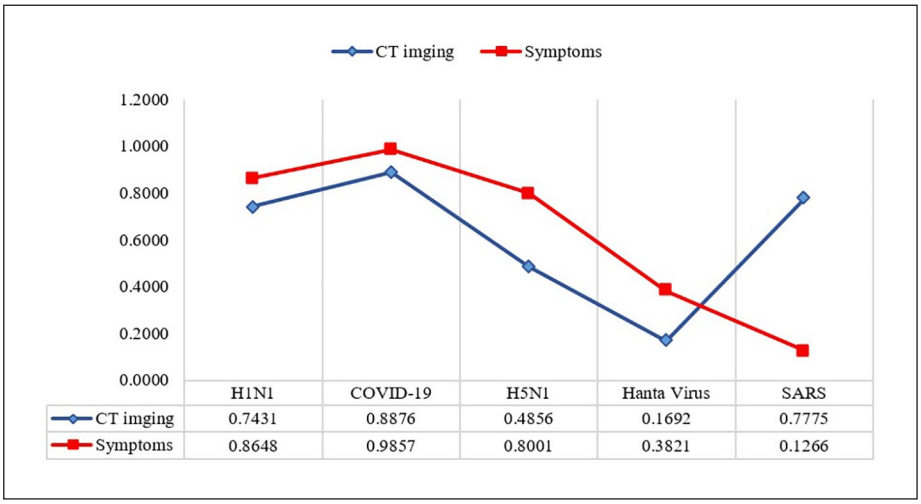
Figure 5. TOPSIS result according to CT imaging.

Figure 6 shows the ranking of the five diseases is almost similar to the one performed according to the common symptoms and the CT imaging results. The doctors' assessment results are based on the fact that COVID-19 is the most prevalent infection of this period. However, the PCR analysis is necessary to prevent any misdiagnosis.

Conclusion

In this article, we proposed an integrated MCDM method under uncertainty environment. This method integrates the benefits of the BWM and TOPSIS to evaluate a set of alternatives according to decision criteria. Experimental evaluation demonstrates the effectiveness of this method by achieving accurate results when applied in a plithogenic environment. To verify the effectiveness of the proposed method, we applied it for the evaluation of five viral chest diseases that exhibit similar symptoms to COVID-19 using their common symptoms and CT imaging results. The plithogenic aggregation operations contradiction degree feature increases the accuracy of the aggregation. Moreover, the TOPSIS is applied based on the weights calculated by the BWM to further improve the reliability of the method.

The future research directions for the study of COVID-19 are many and varied as we continue to learn about the behaviour and characteristics of this virus. By the time we completed this study, the WHO added more symptoms of COVID-19 such as the loss of taste and smell. We plan to repeat our experiments with more symptoms and bigger datasets when they become available. We



	H1N1	COVID-19	H5N1	Hanta Virus	SARS
CT imging	0.7431	0.8876	0.4856	0.1692	0.7775
Symptoms	0.8648	0.9857	0.8001	0.3821	0.1266

Figure 6. Ranking of five diseases according to the symptoms and CT imaging.

also plan to continue the technological developments that aim to compact the spread of COVID-19. Detecting infected cases and tracing people who may be infected is a daunting task in which technology may play an effective role. In this area of study, we intend to explore how adding data from track and trace systems, that is, whether a person came in contact with a COVID-19 patient, could improve the diagnosis accuracy.

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