



Prioritizing severity level of COVID-19 using correlation coefficient and intuitionistic fuzzy logic

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Abstract During the peak of COVID-19 pandemic crisis in 2020 and 2021, with limited medical resources and surge in Covid cases in every hospital and clinic, identifying the most vulnerable patient requiring immediate critical treatment was a great challenge for the medical practitioners. And if such a patient suffers from multiple ailments, his/her condition may deteriorate rapidly if proper treatment is delayed any further. In this paper, we used a novel method which supports medical care units in identifying the patients who need urgent medical treatment. We used Gerstenkorn and Manko correlation coefficient and the intuitionistic fuzzy sets to classify such patients, who should be given the highest priority to start the treatment first. The role of this correlation measurement is very vital in any decision-making process. An intuitionistic fuzzy set (IFS) handles uncertainty, vagueness, ambiguity etc. present in the data and helps in making decision process more realistic. Combining the correlation coefficient with the Intuitionistic fuzzy set makes the decision making process more easy, accurate and reliable. We used COVID-19 dataset which maintains early-stage symptoms of COVID-19 patients, and is publicly available. We applied correlation coefficient and IFS to predict the severity level of the COVID-19 cases by establishing the relationship between the patient and the ailments a COVID-19 patient is suffering from.

Keywords COVID-19 pandemic · Correlation coefficient · Gerstenkorn and Manko correlation coefficient · Uncertainty · Vagueness · Intuitionistic fuzzy sets

1 Introduction

In the real world, the data are often fuzzy in nature which causes problems in the decision making process. To overcome these situations, many fuzzy models which deal with incomplete information present in the form of fuzzy sets are prevalent. Although many problems have been dealt with the fuzzy model which assists and helps the experts in the decision-making process, it is unable to deal with situations where there is hesitation value which corresponds to intuitions of experts not captured by membership and non-membership values. In most of the real-world problems, the hesitation values are present. Therefore, we have used Intuitionistic fuzzy logic (IFL) which takes into consideration the membership value, non-membership value, as well as hesitation value [1, 2]. Intuitionistic Fuzzy Sets (IFS) [3, 4] are said to be a superset of the Fuzzy set. When the hesitation value of an IFS is 0, the IFS set automatically becomes a fuzzy set. IFS was proposed by Prof. Atanassov in 1986. The IFS has been taken up by many researchers and applied in many models and applications.

During the decision-making process, the most important issue is to find the association among the features. To extract the prominent features from dataset, we measure the correlation between them [1, 5–7]. For the proposed work, symptoms are taken from dataset on early-stage symptoms of COVID-19 patients [8]. To deal with this issue, correlation plays a vital role. Correlation coefficient estimates the degree of relationship between two or more

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features. Intuitionistic fuzzy sets are derived from the symptom and ailment relation i.e., Symptom \rightarrow Ailment ($S \rightarrow A$) as mentioned in Table 1, where the IFS values have been allotted in consultation with medical expert as mentioned in the acknowledgement section of this paper. Similarly, the intuitionistic fuzzy sets for patient and symptom are obtained from considered dataset to derive the patient and symptoms relation i.e., Patient \rightarrow Symptom ($P \rightarrow S$) which is mentioned in Table 2. IFS values are taken after the consultation of medical experts. We computed the correlation for the features of the two IFSs, and the computed values show the relations between the ailments and patient through which an expert can make decisions easily about the severity level of the COVID-19, with which a patient is suffering along with other ailments.

In this paper, we have used intuitionistic fuzzy sets and computed the correlations among them for prioritizing the patient who needs urgent treatment.

The paper is organized as follows: Sect. 2 deals with literature review, Sect. 3 gives brief idea of IFS, selection of symptoms, correlation of IFSs, Sect. 4 has details about the algorithm for the experiment, and the result of the experiment are discussed, Sect. 5 discusses conclusions and the scope for future work.

2 Literature review

In research paper [9], the researcher analysed progression of COVID-19 in India, the authors formulated a model which is driven by pandemic data and approximation algorithm by using real data of infection, recovery and death cases. Coefficients of correlations were used for data processing for different Intuitionistic fuzzy sets. N. Chen, Z. Xu & M. Xia [10] derived some correlation coefficient formulae for hesitant fuzzy sets (HFS) which was further applied on clustering technique under the environment of hesitant fuzzy which was applied on software evaluation and classification and the assessment of business failure risk, they developed the interval-valued hesitant fuzzy (IVHF) and the correlation coefficient, and showed the performance in clustering with IVHF information with numerical values. The information of different types of correlation coefficient were discussed in [11], and different formulas were also explained by using

various examples. The researcher in [12] discusses the correlation coefficient, the most used statistical tool which shows the relation, its strength between the IFSs and also gives an idea of how the sets are related either positive or negative. Their method takes membership, non-membership and hesitation values. Many researchers also discussed about the intuitionistic fuzzy correlation measure confined in an algorithm by using membership, non-membership and hesitation values of IFSs. In [13], it estimates the relationship strength which is shown by some theoretical and numerical results which highlights the performance of their method superior to existing correlation measures. The authors in [14] discussed about some advanced techniques which are more superior to the existing coefficient correlation IFSs techniques. Many novel ideas were presented by different researchers in Intuitionistic fuzzy and correlation coefficient, the researcher in [15] presented a new method for correlation coefficient measures for computing the relationship between the two intuitionistic fuzzy sets. The paper in [16] proposed a new correlation measure and its application by embedding it in a Pythagorean fuzzy set (PFS) algorithm for diagnostic processes. It also sees the strength of correlation between PFS which are proved by theoretical results.

With advent of Internet of Things (IoT) and Artificial Intelligence (AI) related techniques, various researchers designed apps to predict if a person is suffering from COVID-19 or not [17]. Researchers have used machine learning algorithms to detect the early stages or symptoms of COVID-19 [18]. In Wuhan city more than 140 patients were tested for the features of COVID-19 [19]. Their clinical features were accessed and analyzed and it was found that 17% patients had acute respiratory distress syndrome, and 11% died due to multi-organ failure [20]. The researchers of [21] have summarized the characteristics and treatments of the COVID-19. The researchers in [22] have studied the online literature related to COVID-19 available on PubMed, google scholar etc. but still the available texts are very few for concrete analysis of COVID-19 disease. Many researchers have suggested medical treatments and characteristics for controlling the outbreak of the pandemic [23]. With the growing concept of IoT, a novel concept emerged to provide the services for the patients suffering from COVID-19 and even for the surgeries [24]. Many new challenges are addressed by the concept of AI by different researchers and

Table 1 Symptoms vs ailments intuitionistic fuzzy relation

S \rightarrow A	a1 (BP)	a2 (Cardiac)	a3 (Surgery)	a4 (Asthma)	a5 (Diabetes)
s1 (lung-infection)	(0.4,0.3,0.3)	(0.2,0.7,0.1)	(0.4,0.4,0.2)	(0.8,0.1,0.1)	(0.3,0.5,0.2)
s2 (pneumonia)	(0.2,0.4,0.6)	(0.6,0.3,0.1)	(0.5,0.3,0.2)	(0.5,0.3,0.2)	(0.3,0.4,0.3)
s3 (cough)	(0.3,0.5,0.2)	(0.3,0.6,0.1)	(0.4,0.5,0.1)	(0.5,0.2,0.3)	(0.4,0.4,0.2)
s4 (runny-nose)	(0.3,0.6,0.1)	(0.3,0.5,0.2)	(0.5,0.3,0.2)	(0.6,0.2,0.2)	(0.4,0.5,0.1)
s5 (fever)	(0.5,0.3,0.2)	(0.6,0.2,0.2)	(0.7,0.2,0.1)	(0.6,0.2,0.2)	(0.4,0.4,0.2)

Table 2 Patient Vs Symptoms intuitionistic fuzzy relation

P → S	s1 (lung-infection)	s2 (pneumonia)	s3 (cough)	s4 (runny-nose)	s5 (fever)
p1	(0.8,0.1,0.1)	(0.6,0.3,0.1)	(0.5,0.3,0.2)	(0.6,0.2,0.2)	(0.7,0.2,0.1)
p2	(0.7,0.1,0.2)	(0.5,0.3,0.2)	(0.4,0.5,0.1)	(0.6,0.3,0.1)	(0.8,0.1,0.1)
p3	(0.6,0.2,0.2)	(0.7,0.1,0.2)	(0.6,0.3,0.1)	(0.5,0.4,0.1)	(0.2,0.6,0.2)
p4	(0.3,0.5,0.2)	(0.6,0.1,0.3)	(0.7,0.1,0.2)	(0.8,0.1,0.1)	(0.4,0.1,0.5)
p5	(0.2,0.7,0.1)	(0.8,0.1,0.1)	(0.1,0.8,0.1)	(0.2,0.7,0.1)	(0.6,0.1,0.3)

scientist. In [25], the researcher discussed the uses of AI to find out the illness and its severity. In [26], the researchers show the automatic infection detection technique by using deep learning approach. In [27–29], video analysis and other procedures help predict the breathing speed and temperature of the patient. The researcher in [30] discussed the details about how the physicians read the medical data or records of a patient suffering from a disease in more confident manner. In [31], the researchers talked about the new COVID-19 app launched by government of India – Aarogya Setu [32] to track the risk of infection spreading among the public rapidly. It also shows the affected area. Many AI and machine learning tools are used to develop models to learn the progress in the COVID-19 cases as well as symptoms, vaccine, drugs related to the virus [33–37]. Many new developed upcoming technologies like drones, robotic, facial recognition software are also used against the novel coronavirus [38]. In [39], researchers show the use of JARVIS, a thermal camera which takes the temperature of the patients remotely. The government is also focusing on the telemedicine usage in the country [40]. Patients already suffering from respiratory problems get much critical due to air pollution [41]. The air pollution problems were analyzed during the COVID-19 lockdown time when a positive change in the environment and relief in the pollution level was observed [42–45]. In the research paper [46], the researcher has proposed a correlation coefficient which ensures that the correlation coefficient between two hesitance fuzzy sets is equal to 1/− 1, if both the hesitance fuzzy sets are same. The researcher in paper [47], proposed a new correlation coefficient between HFSs which lies between [− 1, 1] fulfilling the classical coefficient rules in statistics.

In this section, we reviewed most recent literature related to role of IFS in decision making, and COVID-19 related IoT based apps involving some kind of decision-making processes.

3 Methods

In this section, we have explained all methods used in the proposed work such as Intuitionistic Fuzzy Set and Correlation Coefficient, along with decision making work based on IFS and Correlation.

3.1 Intuitionistic fuzzy set

In the real world, data is mostly fuzzy. For dealing with such fuzziness, Fuzzy logic, introduced by Prof. Lotfi Zadeh in 1965, is used. This logic handles imprecision, vagueness, uncertainty etc. present in the data. At the other side, we have Intuitionistic Fuzzy Logic where apart from uncertainty, imprecision and vagueness, it deals with the hesitation which creeps in during the decision making process which are inherent characteristics of every human intelligence.

The IFS concept is very flexible and it gives more freedom than a fuzzy set in decision making. It is very efficient and effective in expressing any argument/state-ment in linguistic expression as it takes hesitation values along with the membership and non-membership values [2]. The IFS includes the intuition of the experts based on their experience which excludes the biases and helps in diagnosing and finding the severity of the disease.

We represent Intuitionistic Fuzzy Set as:

Let A an Intuitionistic Fuzzy Set and in a universe of discourse X,

$$A = \{(x, \mu_A(x), \nu_A(x)) \mid x \in X\}$$

where,

$\mu_A(x)$: X \in [0, 1] is the membership degree between 0 and 1 of element $x \in X$ in IFS A.

$\nu_A(x)$: X \rightarrow [0, 1][0, 1] is the non-membership degree between 0 and 1 of element $x \in X$ in IFS A. The value of membership and non-membership is $0 \leq \mu_A(x) + \nu_A(x) \leq 1$ for all $x \in X$. In IFS along with membership and non-membership value, we also have hesitation value which is represented as [48]:

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$$

where $0 \leq \mu_A(x) \leq 1$ for all $x \in X$.

In our experiment, we have intuitionistic fuzzy sets A and B which are derived from Tables 1 and 2. Table 1 is the relation between ailments and symptoms of COVID-19 and Table 2 has information of patients and symptoms. All patients are suffering from COVID-19 and other ailments too.

The degree of relationship between two IFS is measured through the correlation coefficient analysis. This measure is called the correlation coefficient. Correlation values lie

between $[-1, 1]$, where -1 is pure negative correlation, $+1$ is pure positive correlation and 0 is no correlation between the variables. It shows the strength and direction of the relation between the variables or attributes. It is important to know the strength between the variables or attributes. The stronger the correlation, the correlation coefficient is closer to $+1$ or -1 . It is an important measure for data analysis used in the decision making or medical diagnosis process for the real-world problem. It helps in getting us similarity, interdependability, and interrelation among the variables or attributes. It has been used in many fields because of its potential applications. Some researchers used correlation measures with the fuzzy set to handle fuzzy data. Amalgamation of correlation with Intuitionistic Fuzzy sets are used to make decisions robust [3, 6].

3.2 Correlation of two ifs sets

Correlation can be measured and computed in many ways like graphical way- scatter plot, graph methods etc. It can be measured in a mathematical way also like Karl Pearson's method, Rank Method, Concurrent Deviations Method etc. Correlation measure and intuitionistic fuzzy sets play an important role to tackle the fuzziness present in the decision making process. To find the correlation between intuitionistic fuzzy sets, Gerstenkorn and Manko, in 1991, developed the correlation coefficient between IFSs [7] which we have extended for the proposed work.

The proposed method helps the practitioners to predict the most vulnerable patient's case which will help in identification of patients requiring the immediate attention of doctors and quick availability of the medical treatments. This way it alerts the experts so that they could provide proper care to the patient as soon as possible because delay in providing them the treatment makes the patient's case pathetic.

We computed the correlation coefficient of two IFS sets. The higher the correlation coefficient, the stronger chance of being critical case of the patient.

The Gerstenkorn and Manko formula for correlation coefficient for intuitionistic fuzzy set is defined in Eq. (1) [4, 7].

$$CC(X, Y) = C(X, Y) / [R(X) \times R(Y)]^{1/2} \quad (1)$$

where X and Y are two IFS sets and $C(X, Y)$ is the correlation of the Intuitionistic Fuzzy Sets X and Y . The correlation $C(X, Y)$ is computed as given by Eq. (2).

$$C(X, Y) = \sum_{i=1}^N (([\mu_X(x_i) \times \mu_Y(x_i) + [v_X(x_i) \times v_Y(x_i)] + [\pi_X(x_i) \times \pi_Y(x_i)]]) \quad (2)$$

$\mu_X(x_i)$: Membership value of IFS Set X ; $v_X(x_i)$: Non-membership value of IFS set X ; $\pi_X(x_i)$: Hesitation value of IFS set X

$\mu_Y(x_i)$: Membership value of IFS Set Y ; $v_Y(x_i)$: Non-membership value of IFS set Y ; $\pi_Y(x_i)$: Hesitation value of IFS set Y .

and $R(X)$ and $R(Y)$ are defined in Eqs. (3) and (4) [7]:

$$R(X) = \sum_{i=1}^N [(\mu_X^2(x_i) + v_X^2(x_i) + \pi_X^2(x_i)), \text{ for IFS set } X \quad (3)$$

$$R(Y) = \sum_{i=1}^N [(\mu_Y^2(x_i) + v_Y^2(x_i) + \pi_Y^2(x_i)), \text{ for IFS set } Y \quad (4)$$

We propose an algorithm mentioned below in order to achieve more applicability of the method:

Algorithm: Covid_Severity_Level

1. $List_of_symptoms := symptoms$;
 2. Repeat step 3 until $List_of_symptoms$ is empty
 3. Select prominent symptoms
 - a. If $correlation_{S[i]} > correlation_{S[j]}$
select prominent symptom $S[i]$
 - b. If $correlation_{S[i]} = correlation_{S[j]}$
Select symptom $S[i]$ or symptom $S[j]$;
 $i := symptom\ index; prominent\ symptom := S[i]$;
 4. Construct IFS relation T_{SA} between prominent symptom and ailment i.e., IFS set X .
 5. Construct IFS relation T_{SP} between prominent symptom and patient i.e., IFS set Y .
 6. Calculate correlation coefficient $CC(X, Y)$ for T_{SA} and T_{SP} .
 $CC(X, Y) = C(X, Y) / [R(X) * R(Y)]^{1/2}$
 7. Determine $\sum_{p_i, a_i}^{i=n} CC(X, Y)$ for each patient $p[i]$ and corresponding ailments $a[i]$.
 8. Determine $\text{Max} [\sum_{p_i, a_i}^{i=n} CC(X, Y)]$ for finding the most critical case.
-

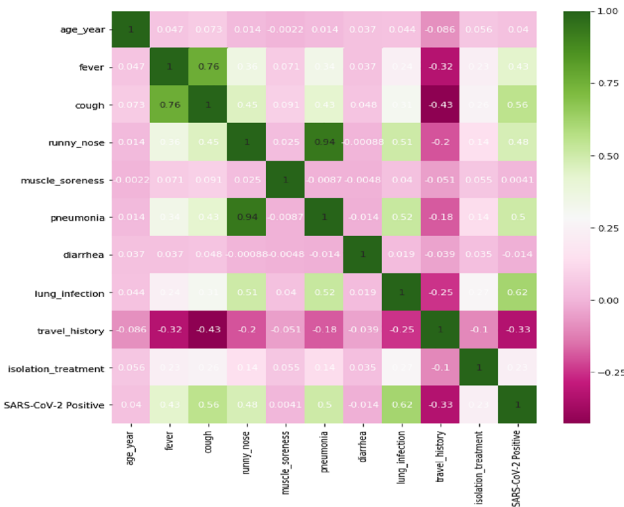


Fig. 1 Correlation between the symptoms shown by heatmap

3.3 Correlation v/s distance measures

During decision making process, distance measure is not suitable in case of large dataset specially with large number of features. In case of higher dimensional data, distance measures may assume the dependent features as uncorrelated. As the dimensionality increases, the distance measures becomes less relevant [49–51].

Correlation coefficient quantifies the strength of relation between two variables. Most commonly distance measure is used to find out which of the IFS sets are close to each other but computing distance may be memory intensive for high dimensional datasets. Distance measurement does not provide information how strongly the variables are associated but correlation does so. It ranges with values lying between - 1 to 1. We have used correlation measure in our algorithm which makes it efficient. In paper [49], distance measure is used which might have issues discussed above in case of large and high dimensional dataset.

4 Proposed decision making system for prioritizing severity level in COVID-19 patients

The database used in this paper is related to COVID-19 which is used to extract the most prominent symptoms in the Covid patients. The severity of COVID-19 increases if a patient suffers from chronic ailments such as Diabetes, Surgical issues, Asthma, Blood Pressure, Cardiac etc.; and henceforth the risk of morbidity of such patients also increases. Any such ailments affect the COVID-19 case very differently; and combinations of these ailments deteriorate the covid-case further. In such situation, physicians get confused how to determine which patient’s case is most vulnerable, and with limited medical resources which patients should be given highest priority for providing the medical facility. Providing the medical facilities becomes a difficult decision if the resources are very limited as we had seen during the second wave of COVID-19 in India during April 15 to May 5, 2021 when many patients died due to unavailability of hospital beds and oxygen therapy.

4.1 Symptom selection from the disease dataset

Heatmap depicts how the symptoms are correlated to each other with respect to target label from covid dataset (Kaggle dataset on early-stage symptoms of COVID-19 patients) [8]. The heatmap in Fig. 1 explains the correlation among symptoms of COVID-19 (SARS-CoV-2). The first five most correlated symptoms for COVID-19 are lung-infection, pneumonia, cough, runny-nose, and fever. Therefore, we take these five symptoms in our experiment.

4.2 Experiments and results

The proposed method is explained for 5 patients, p1, p2, p3, p4, and p5 from the considered dataset. The corresponding tables consist of the Intuitionistic Fuzzy values with its membership value, non-membership value and hesitation value. Table 1 shows the symptoms and ailment of COVID-19 in terms of intuitionistic fuzzy values; while

Table 3 Result of correlation coefficient of IFSs

	a1	a2	a3	a4	a5	D = a1 + a2 + a3 + a4 + a5
p1	0.80	0.60	0.89	0.71	0.95	3.95
p2	0.42	0.97	0.97	0.83	0.96	4.15
p3	0.90	0.77	0.90	0.97	0.58	4.12
p4	0.72	0.92	0.95	0.96	0.83	4.38
p5	0.95	0.66	0.79	0.91	0.85	4.12

Table 2 shows the IFS values for patient and symptom. Here, we selected highly correlated symptoms from considered dataset, which are lung-infection (s1), pneumonia(s2), cough(s3), runny-nose(s4), and fever(s5) as found in Sect. 4.1. The symptom-ailments intuitionistic fuzzy relation $S \rightarrow A$ is given in Table 1.

The value of IFS membership and non-membership for Tables 1 and 2 have been mentioned as per the consultation of medical expert for five patients p1, p2, p3, p4, p5 suffering from COVID-19 along with the other ailments, as discussed, with highly correlated symptoms. The Patient-Symptoms intuitionistic fuzzy relation $P \rightarrow S$ is given in Table 2.

From these two tables we computed the correlation coefficient and which we used to predict the patient who is most likely to be given the immediate treatment. Such a system is very useful in assisting the experts in the decision-making process. The correlation coefficient between the Intuitionistic Fuzzy set is computed as follows:

The value of $C(X,Y)$, $R(X)$, and $R(Y)$ are obtained from Eqs. (2), (3), and (4). These values are put in Eq. (1) for computing the correlation coefficient i.e. $CC(X,Y)$ between the two IFS sets for Table 1 ($S \rightarrow A$) and Table 2 ($P \rightarrow S$), we get the result in Table 3 ($P \rightarrow A$) with ailment and patient. After calculating the values for correlation coefficient of the Intuitionistic Fuzzy relations, these values are added for all the symptoms of the patients. Higher the value (D), higher the severity level of disease in that patient. Hence, it is possible to make distinction between the patients who are more severe than the others and need urgent care.

By looking at Table 3, it is clear that the patient p4 where $D = 4.38$ is more critical and needs immediate attention and treatment. The higher the value of D (sum of all correlation values) [49], the higher the severity of COVID-19 the patient suffers from; and so he/she needs critical care attention with the highest priority.

5 Conclusions and future scope

Correlation Coefficient between two IFS sets (Symptoms \rightarrow Ailment & Patient \rightarrow Symptoms) is an important index or metric for describing the degree of association between the given sets as well as finding how intuitionistic fuzzy sets are correlated. This helps in decision making process. We can use it in the medical field in cases where a patient is suffering from multiple diseases and the doctor has to decide how emergently handle such a case with respect to limited resources, and whom to give the priority. The proposed method is simple and user friendly. A new medical practitioner can use it without waiting for expert opinion in case of an emergency such as COVID-19

happened during the second wave in India during April–May 2021. This technique or approach may be applied for other situations where priority is to be decided. As a future work, we will do cloud-based implementation of the proposed model which will make it easily available everywhere.

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