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RESEARCH ARTICLE

USING INTUITIONISTIC FUZZY C-MEANS CLUSTERING ALGORITHMS TO MODEL COVID-19 CASES FOR COUNTRIES IN THE WORLDWIDE

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ABSTRACT

Every day, the number of newly confirmed cases of coronavirus (COVID-19) rises in many countries. It is critical to adjust policies and plans in order to investigate the relationships between the distributions of the spread of this virus in other countries. During this study, the intuitionistic fuzzy c-means (IFCM) clustering method is used to compare and cluster the distributions of COVID-19 spread in 62 countries. Using the IFCM clustering algorithm, the study aims to cluster the countries that use environmental, economic, social, health, and related measurements that affect disease spread to implement policies that regulate disease spread. As a result, countries that have similar factors can take proactive measures to address the pandemic. The data are obtained for 62 countries, and six different feature variables (factors associated with the spread of COVID-19) are determined. The data are obtained for 62 countries, and six variables with different characteristics (linked to the spread of COVID-19) are identified. In this study, the IFCM clustering algorithm is used to determine the dynamic behavior of COVID-19 based on real-world data for multiple countries and Turkey around the world. Data analysis is performed through MATLAB 2018a and R programs. The clustering results revealed that the distribution of dissemination in Brazil, India, and the United States was nearly identical and distinct from that of the 59 other countries.

Keywords: Intuitionistic fuzzy sets, Fuzzy C-means clustering algorithm, COVID-19, Statistical analysis

1. INTRODUCTION

According to some sources, the world has been dealing with a massive epidemic of unprecedented proportions since December-November 2019. The epidemic is said to have occurred in late December 2019. After "Coronavirus Disease 2019 (COVID-19)" was stated, a new type of coronavirus, "Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2)", was defined, as SARS-CoV-2 causes a spectrum of disease. COVID-19 is expanding rapidly worldwide due to its high contagiousness. Since November or December 2019, according to some sources, the COVID-19 pandemic originated in Wuhan, the seventh largest city in China, from where it has spread and continues to spread throughout the world. On March 11, 2020, sometime after the COVID-19 pandemic outbreak, the World Health Organization (WHO) declared the outbreak an epidemic. The quick dissemination of the COVID-19 epidemic has aroused a lot of countries around the world to take strict measures to limit the free movement of their citizens. Taken the measures have affected overall segments of society and there are difficulties for economic and social life. Downward movements in the basic economic and financial indicators were noted in this period. On the contrary, lots of scientists from different fields have attempted to gather data on this pandemic-level disease and uncover useful findings in the light of this data. At the same time, the WHO and OECD, as well as universities and various non-governmental organizations, provide a rapid flow of data on the epidemic, effectively informing societies and researchers.

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Many researchers have attempted to reduce the spread of COVID-19 in the literature since its inception. Therefore, a rapidly growing literature, especially in fuzzy clustering algorithms, has formed since the first time the COVID-19 outbreak appeared.

Fuzzy clustering algorithms reveal fuzzy partitions where observations can be roughly assigned to one cluster. Bezdek (1981) suggested fuzzy C-means (FCM) clustering, which is one of the most widely utilized fuzzy clustering algorithms [1]. Nevertheless, there is a basic disadvantage to this algorithm, which is its sensitivity to noise and outliers. In order to deal with wrongfully stated data as well as imprecise knowledge and facts, intuitionistic fuzzy set may be an effective tool. An IFCM that is a stretched version of this method is offered by Zhang and Chen (2007), Xu, Chen, and Wu (2008), and Chaira (2011) [2-4]. Also, a clustering algorithm supported by IFS is presented by R. Bhargava et al. [5]. The applications of IFCM were demonstrated in a few recently published papers (see [6-10]). Finally, the convergence theorem of IFCM was recently provided by Lohani et al. [11], and other sorts of convergence are disputed by them in [12-14].

In recent years, thanks to the big application areas of IFCM, it has developed quite well-liked algorithms, and there are also many interesting applications in areas biology, medicine, engineering, economics and finance [14-21]. It should be noted that the FCM clustering algorithms have been studied since the first time the COVID-19 outbreak appeared in the literature. Due to the use of the fuzzy clustering method, which allows them to be grouped in accordance with the resemblance of the characteristics and structures of time series, which set the dynamics of the epidemic process in them, a bibliographical investigation revealed that the COVID-19 pandemic has analogue patterns of development in various countries [22-24]. It can be summarized that, depending on the analysis, patterns in the incidence of coronavirus infection are administered to small groups of geographical countries or regions. M.R. Mahmoudi et al. (2020) [22] compared the rate of spread of COVID-19 in high-risk countries using a fuzzy clustering system. W. Dink et al. (2020) investigated the possibility of early detection of COVID-19 from radiographic images using unsupervised fuzzy clustering [23]. O. Castillo and P. Melin (2021) used a novel clustering method based on an intelligent fuzzy fractal approach to investigate COVID-19 data [24].

Our study is one of the first in the literature, in connection with the COVID-19 pandemic, to implement IFCM clustering. For such a high-dimensional grouping problem with many missing values, fuzzy clustering methods such as fuzzy C-means clustering are not very effective. In this study, we use the IFCM clustering method. Our primary objective is to provide an intuitionistic fuzzy C-means cluster analysis of 62 countries worldwide based on the cumulative confirmed COVID-19 cases, cumulative confirmed COVID-19 deaths, life expectancy, human development index, fatality rate, and population density using by IFCM algorithm.

The aim of this paper is to provide a dynamic structure for summarizing status and analysis results for countries both globally and in Turkey using current COVID-19 data. Moreover, this research allows us to track the daily flow, movement, and changes in cases and deaths around the world and on a country-by-country basis as descriptive statistics related to COVID-19 on a graph.

The rest of the paper is organized as follows: a short introduction to intuitionistic fuzzy sets is given in Section 2. The methodology of the intuitionistic fuzzy C-means clustering algorithm is offered in Section 3. Section 4 presents an application of intuitionistic fuzzy C-means clustering algorithms to model COVID-19 cases for countries worldwide. Finally, the essential results evaluated during this study are summarized, and a few proposals for further research are attributed in Section 5.

2. INTUITIONISTIC FUZZY SETS (IFS)

Zadeh (1965) established fuzzy set theory as elements have differentiating degrees of membership, which an extension of classical set theory [25]. The basic idea of this theory is to treat uncertainty using membership values. Here, it may not always be adequate as the membership values. Atanassov (1986) suggested a generalization of fuzzy sets as intuitionistic fuzzy sets [26]. An additional uncertainty parameter, which is the hesitation degree, is also debated in the IFS theory. In clustering, there has been a prevalent study of the intuitionistic fuzzy set theory, which is constantly utilized as a method due to simplicity and its flexibility within the literature.

Each fuzzy element x in IFS is assigned a membership value and a non-membership value with some hesitancy, and this hesitancy is caused by incomplete information about x. As a result, it cannot forecast a more precise membership and non-membership value. As a result, both the membership value and the non-membership value specified in$x$may be incorrect. Mathematically, an intuitionistic fuzzy set A in X, is introduced as follows:

$$A = \{x, \mu_A(x)\,, v_A(x)\ / x \in X\}$$

where $\mu_A(x) \to [0,1]$, $v_A(x) \to [0,1]$are the membership and non-membership degrees of an element$x$ in the set A with the condition

$$0 \le \mu_A(x) + v_A(x) \le 1$$

When $v_A(x) = 1 - \mu_A(x)$for each x in set A, the set A becomes fuzzy. In addition, Atanassov demonstrated a hesitation degree,$\pi_A(x)$, which appears due to a lack of knowledge in defining the membership degree of each element x in set A for all intuitionistic fuzzy sets, and is introduced by:

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

where it is clear that $0 \le \pi_A(x) \le 1$. Because of the hesitation level, the membership values reach out in the interval; $[\mu_A(x), \mu_A(x) + \pi_A(x)]$. If $\pi_A(x) = 0$, then $v_A(x) = 1 - \mu_A(x)$. Thus, A reduces to a fuzzy set [4].

3. IFCM CLUSTERING ALGORITHM

Clustering analysis is a statistical method that allows you to describe the common characteristics of the units, collecting the units examined in a study according to their similarities. Fuzzy clustering analysis helps cope with the uncertainty of real numbers to reveal appropriate clustering models for daily life experience. One of the most prevalent blurred clustering algorithms is fuzzy C-means (FCM) clustering. However, this algorithm has one main drawback, which is the noise and, on the contrary, the sensitivity of the values. The intuitionistic fuzzy C-means (IFCM) clustering is a proper tool for dealing with flawlessly given facts, data, and non-precision information. Chaira's method is utilized, and its algorithm in this study is defined as follows:

Algorithm: Intuitionistic Fuzzy C-Means Clustering Algorithm
The IFCM algorithm's first task is to transform crisp data into fuzzy data, which is then transformed into intuitionistic fuzzy data.
Step 1. $u_{ik}, i = 1,2,\dots,c; k = 1,2,\dots,n$ is the membership value of k^{th} data in i^{th} cluster.
The parameters are used to generate $r_{ik}, i = 1,2,\dots,c; k = 1,2,\dots,n$ values from a uniform distribution (0,1). The membership values are calculated using Eq. (1).

$$u_{ik} = \frac{r_{ik}}{\sum_{i=1}^{c} r_{ik}} \tag{1}$$

Step 2. Eqs. (2) and (3) are used to compute the hesitation degree (π_{ik}) and intuitionistic fuzzy membership (u_{ik}^{*}) values, in turn

$$\pi_{ik} = 1 - u_{ik} - (1 - u_{ik}^{\alpha})^{1/\alpha}, \alpha > 0 \tag{2}$$

$$u_{ik}^{*} = u_{ik} + \pi_{ik} \tag{3}$$

The intuitionistic membership values (u_{ik}^{*}) are kept in U_{old} matrix.

Step 3. Centers of clusters (v_i^{*}) are computed by taking Eq. (4)

$$v_i^{*} = \frac{(u_{ik}^{*})^{m} x_k}{\sum_{k=1}^{n} (u_{ik}^{*})^{m}}; i = 1,2,\dots,c \tag{4}$$

x_k is the k^{th} data and m is the fuzziness index.

Step 4. The membership values are get up to date with taking Eq. (5)

$$u_{ik} = \frac{1}{\sum_{k=1}^{n} \left(\frac{d_{ik}}{d_{jk}}\right)^{2/(m-1)}}; i = 1,2,\dots,c; k = 1,2,\dots,n \tag{5}$$

where d_{ik} is the Euclidean distance measure between k^{th} data in i^{th} clustercenter and using Eq. (6) it is computed as:

$$d_{ik} = \sqrt{\left(x_k - v_i^{*}\right)^2} \tag{6}$$

Step 5. Hesitation degree (π_{ik}) and intuitionistic fuzzy membership (u_{ik}^{*}) values are updated in turn using Eqs. (2) and (3). The novel intuitionistic membership (u_{ik}^{*}) values are retained in the U new matrix.

Step 6. Stopping criteria is controlled.

4. APPLICATION

The WHO defines an outbreak as the extensive spread of a recent disease, [12]. Since December 2019, there has been a significant report about over 167 million confirmed cases and 3.46 million total deaths from COVID-19. Furthermore, because it spreads very promptly and expands readily, COVID-19 may be a mortal virus. So, resulting in less confidence within the economic process and a sharp comeback in investment, the prevalent outbreaks have a deep historical impression on economic and social development.

During this application, we use the IFCM clustering algorithm for the 62 countries consistent with the basic variables associated with the COVID-19 pandemic. Data are observed over time, spanning from the first week of January 2020 to the last week of August 2021 [27].Then, in the dataset, the relationship between the attributes (variables) is addressed, and the results obtained from clustering analysis are given. The data set includes date, numbers of cumulative confirmed COVID-19cases and deaths, country name, country code, continental information, human development index from 1980 to 2017, population density from 1961 to 2017, life expectancy from 1543 to 2015, fatality rate.

In addition, additional attributes detailed below are calculated and added to the data set in order to better identify their similarities to the COVID-19 outbreak in clustering analysis, regardless of the geographical location of the countries. These qualities were expected to strengthen the IFCM clustering analysis. The main reasons why we prefer this algorithm are its simplicity, flexibility, and low computational complexity. The algorithm is obtained through cluster validity measures.

Because of the many dangers, the speed at which COVID-19 spreads requires particularly stringent policies and plans. Accordingly, it is very important to study the relationships between the breakdowns and the spread of this virus in other countries.

4.1. Data Sources

The distributions of the spread of COVID-19 in Austria, Azerbaijan, Australia, Bosnia and Herzegovina, Belgium, China, Costa Rica, Czech, Canada, Cyprus, Cuba, Denmark, Ethiopia, Ecuador, Egypt, France, Greece, Germany, Finland, Hungary, Indonesia, Iceland, Iraq, Israel, Ireland, Italy, Iran, Kazakhstan, Kenya, Japan, Malaysia, Norway, Mexico, Maldives, New Zealand, Nigeria, Netherlands, Pakistan, Palestine, Philippines, Peru, Portugal, Poland, Russia, Romania, Qatar, Switzerland, Saudi Arabia, South Korea, Sweden, Slovakia, South Africa, Slovenia, Ukraine, United Kingdom, Spain, Vietnam Venezuela, Turkey, Brazil, India, United States are compared and clustered using IFCM clustering technique. To study the relations of the distributions of the spread of COVID-19 among cumulative confirmed COVID-19 cases and deaths, human development index, population density, life expectancy and fatality rate are used and illustrated in Table 1.

Table 1. Used variables of the distributions of the spread of COVID-19

Variables ID	Variables
X_1	Cumulative confirmed COVID-19 cases
X_2	Cumulative confirmed COVID-19deaths
X_3	Life expectancy
X_4	Human development index
X_5	Fatality rate
X_6	Population density

The IFCM clustering analysis used six different variables, which are as follows and illustrated in detail in Figures 1-6. The figures are plotted by the R program.

Cumulative confirmed COVID-19 cases: The number of confirmed cases is more detailed than the total cases. The basis for this is testing.

Cumulative confirmed COVID-19 deaths: Limited tests and difficulties in determining the cause of death lead to the conclusion that the number of confirmed deaths cannot be an accurate count of the actual number of deaths caused by COVID-19.

Life expectancy: Life expectancy is the key metric for assessing population health. Life expectancy, which is wider than the narrow metric of infant and child mortality, which focuses only on mortality at a young age, captures mortality over the entire course of life. He tells us the typical age of death in the overpopulation.

Human development index: The Human Development Index (HDI) is a summarizing measure of average success in the three major aspects of human growth: having to live a healthy and long life, being knowledgeable, and having a reasonable standard of living. It is determined by:

- Average Life Expectancy at Birth
- Average and Projected Years of Schooling
- GNP for Each Head of Population (in PPP-adapted international dollars)

The HDI is the geometric mean of normalized indices for each of the three dimensions.

Fatality rate: The case fatality rate (CFR) is the ratio of confirmed deaths to confirmed cases. CFR can be a poor predictor of disease-related mortality.

Population density: The number of people per km² of land area [27].

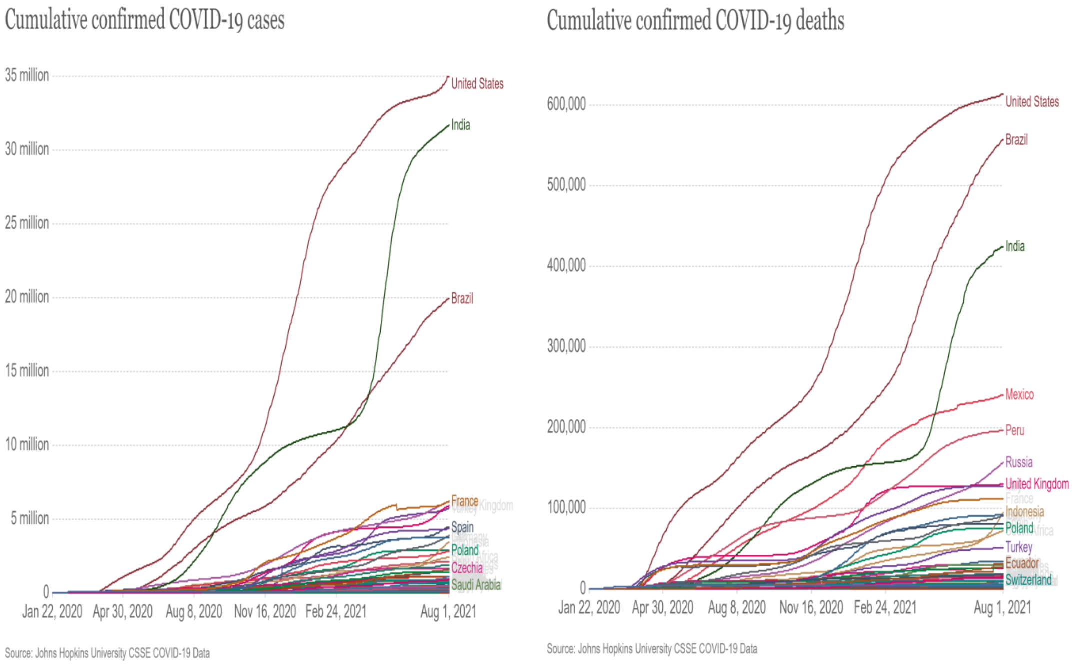

Figure 1. Plots of the variables of COVID-19 data set [28]

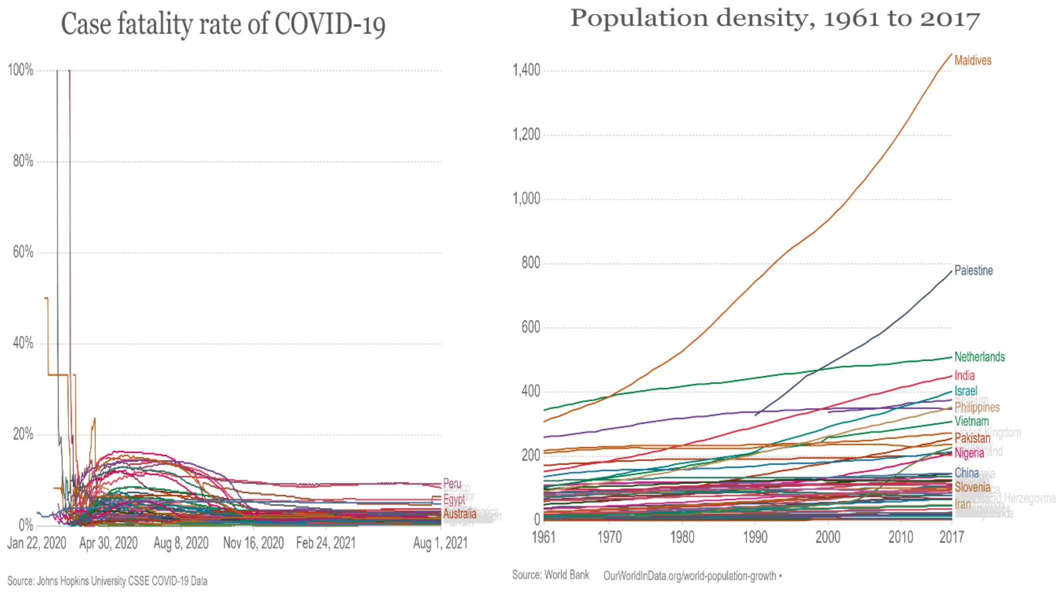

Figure 2. Plots of the variables of COVID-19 data set [28-29]

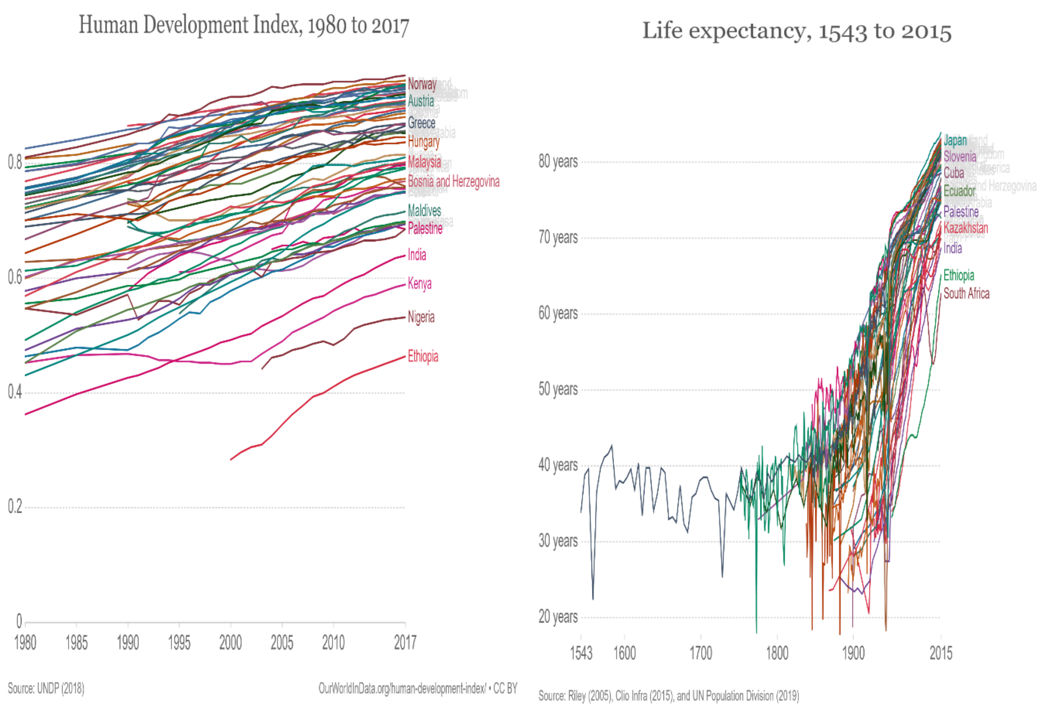

Figure 3. Plots of the variables of COVID-19 data set [30-31]

The graphs in Section 4, plotted the statistics related to the mentioned variables and the list of 62 COVID-19 affected countries until August 2021.

When we examined the number of cases, deaths, and case mortality rates from January 2020 to August 2021, the top 10 countries in the world were constantly displaced, especially Spain, Italy, Germany, France, Canada, and Turkey, while the increases were controlled, because the highest number of cases and deaths were in the USA, Brazil, and India which topped all countries in the world.

The situation of the graph comparing the number of cases and deaths in the countries is supported in Figure 4. Similarly, in Figure 5, where the number of deaths and case mortality rates are compared in the countries themselves, and in Figure 6, where the population density and number of deaths of countries are compared, the countries of the USA, Brazil, and India show proximity to each other.

It can be said that Turkey tends from critical to good due to the fact that case fatality rates are low compared to other countries, as well as the number of days needed to double the number of cases.

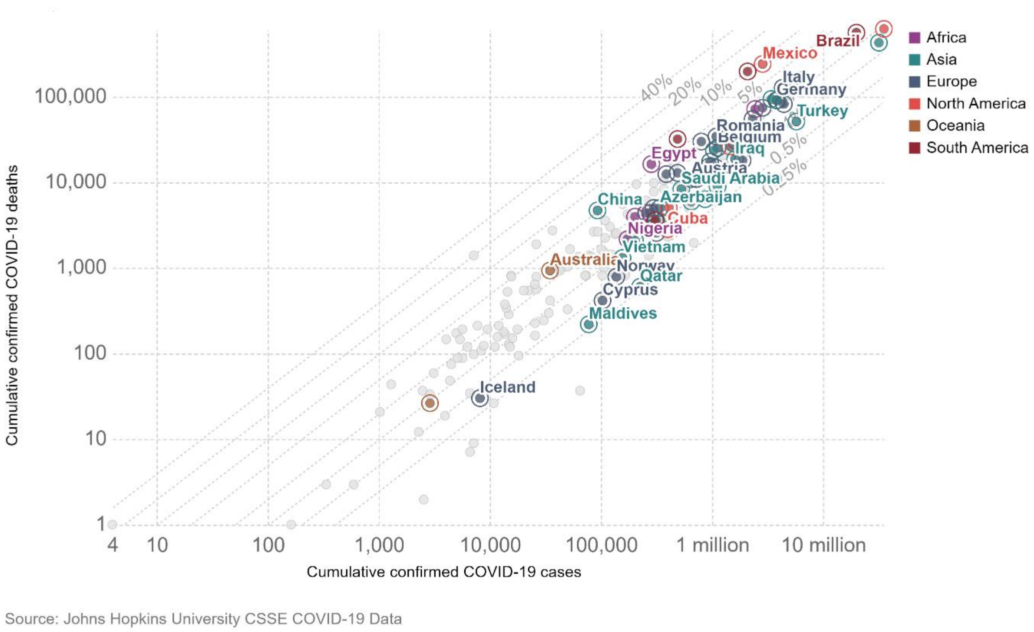

Figure 4. Comparison of cumulative confirmed COVID-19 cases and deaths [28]

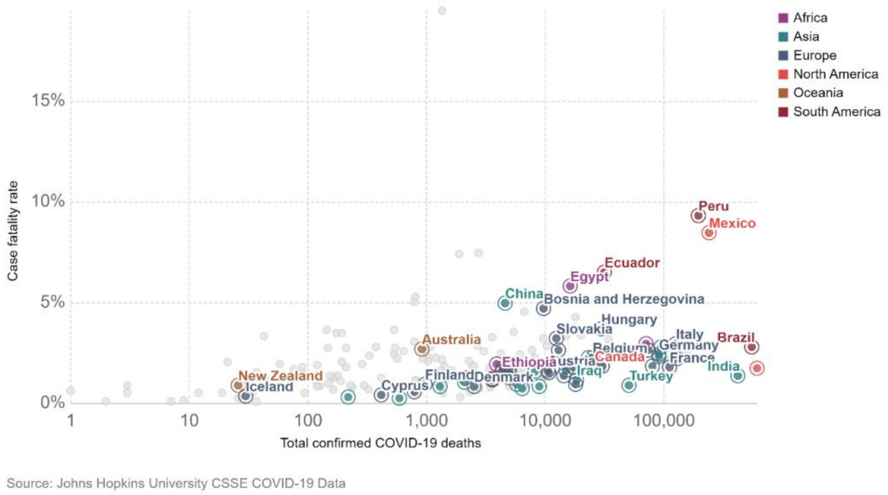

Figure 5. Comparison of cumulative confirmed COVID-19 deaths and case fatality rate [28]

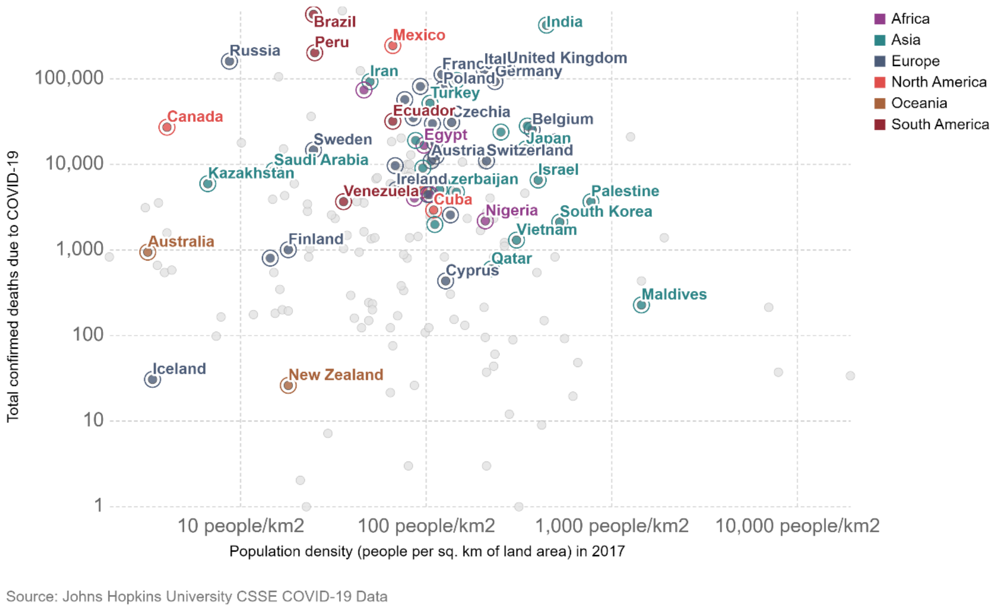

Figure 6. Comparison of cumulative confirmed COVID-19 deaths and population density [28]

4.2. Comparing of the Performances of Validity Indices

To test validity indices during a prevalent used genetics data set, comparing of defined indices above are finished the IFCM clustering algorithm. In total, different values for the fuzzier parameter in the algorithm were used, and the impact of the cluster number of adjusting values was observed. The test for convergence within the IFCM clustering algorithm was performed using $\varepsilon = 10^{-5}$, and also the distance function $\|.\|$ was defined as Euclidean distance, iteration number=100 and $c = 2$.

For the application, MATLAB 2018a, which is an environment for statistical computing program, was used. In an attempt to apply the algorithm, the initial parameters (excluding the quantity of clusters) were chosen randomly. It should be noted that the clustering quality or performance of a clustering algorithm is mostly evaluated by using the internal validity indices. In this paper, classification entropy (CE), the partition coefficient (PC), and the modificatedpartititon coefficient (MPC) results were calculated to work out the quantity of clusters. Apart from the MPC and PC validity indices using the maximum value, the optimum cluster result may be determined by the minimum index value in classification entropy (CE). In Table 2, the validation indices are given with respect to the number of clusters.

Table 2. Values of Validity Indices for IFCM Algorithm

Cluster Number	PC	MPC	CE
2	1.096	1.192	0.364
3	1.083	1.125	0.730
4	1.028	1.038	1.100
5	0.423	0.278	1.289
6	0.410	0.292	1.575
7	0.864	0.841	1.911
8	0.350	0.257	2.069
9	0.801	0.776	2.313
10	0.318	0.242	2.436

Since $c = 2$, PC and MPC reach its optimal (maximum) value 1.096 and 1.193, and CE also gets through its optimal (minimum) value 0.364 can be demonstrated in Table 2. In other words, PC, MPC and CE are up to find the optimal number of clusters as $c = 2$.

4.3. The IFCM Clustering Analysis

The number of clusters has been designated as 2. The clusters according to the countries are given in Table 3as a result of the IFCM clustering analysis

Table 3. Clusters according to the countries

Cluster 1	Cluster 2
Austria, Azerbaijan, Australia, Belgium, Bosnia and Herzegovina, China, Costa Rica, Canada, Czech, Cyprus, Cuba, Denmark, Ethiopia, Ecuador, Egypt, France, Greece, Germany, Finland, Hungary, Indonesia, Iceland, Iraq, Israel, Ireland, Italy, Iran, Kazakhstan, Kenya, Japan, Malaysia, Norway, Mexico, Maldives, New Zealand, Nigeria, Netherlands, Pakistan, Palestine, Philippines, Peru, Portugal, Poland, Russia, Romania, Qatar, Switzerland, Saudi Arabia, South Korea, Sweden, Slovakia, South Africa, Slovenia, Ukraine, United Kingdom, Spain, Vietnam Venezuela, Turkey	Brazil, India, United States

To identify the number of clusters, PC, CE, and MPC validity indexes are used. Table 3 and Figure 7 ensure the fuzzy clustering technique results Table 3 and Figure 7 show how the number of cumulative confirmed COVID-19 cases and deaths, human development index, population density, life expectancy, and fatality rate in the 62 countries studied can be divided into two clusters. Based upon these values, the first cluster consists of Austria, Azerbaijan, Australia, Belgium, Bosnia and

Herzegovina, China, Costa Rica, Canada, Czech, Cyprus, Cuba, Denmark, Ethiopia, Ecuador, Egypt, France, Greece, Germany, Finland, Hungary, Indonesia, Iceland, Iraq, Israel, Ireland, Italy, Iran, Kazakhstan, Kenya, Japan, Malaysia, Norway, Mexico, Maldives, New Zealand, Nigeria, Netherlands, Pakistan, Palestine, Philippines, Peru, Portugal, Poland, Russia, Romania, Qatar, Switzerland, Saudi Arabia, South Korea, Sweden, Slovakia, South Africa, Slovenia, Ukraine, United Kingdom, Spain, Vietnam Venezuela, Turkey (with probabilities 0.76, 0.98, 0.63, 0.88, 0.94, 0.72, 0.38, 0.87, 0.18, 0.14, 0.84, 0.89, 0.61, 0.92, 0.59, 0.857, 0.07, 0.94, 0.92, 0.63, 0.38, 0.57, 0.44 ,0.26, 0.76, 0.64, 0.65, 0.95, 0.95, 0.56, 0.65, 0.75, 0.38, 0.48, 0.81, 0.65, 0.23, 0.41, 0.91, 0.11, 0.71, 0.46,0.28, 0.76, 0.92, 0.66, 0.60, 0.61, 0.96, 0.93, 0.77, 0.54, 0.34, 0.24, 0.72, 0.66, 0.77, 0.99, 0.34). Brazil, India, and the United States are also part of the second cluster (with probabilities 0.85, 0.99, 0.97).

Scattering of the clusters which are acquired as a result of IFCM clustering algorithm are shown in Figure 7.

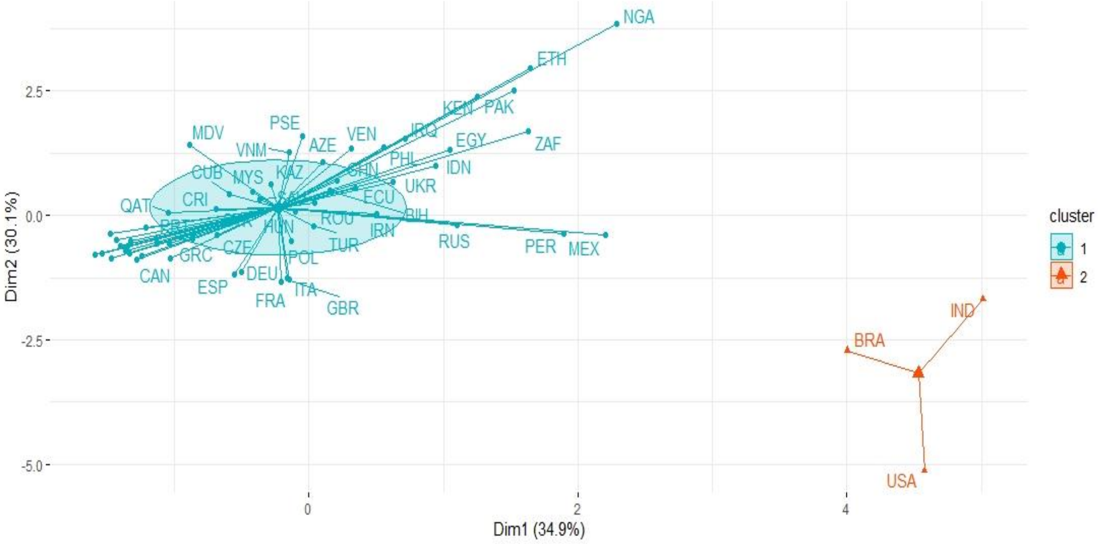

Figure 7. Plot of clustered COVID-19 data set with IFCM clustering algorithm

The grouping (clustering) of countries based on their similarities is one of the most important analyses of this study, and the results that can come from here can lead to cooperation and joint decisions on the measures and methods to be taken. The IFCM clustering analysis revealed.

According to statistical graphs of variables given in Section 4.1, the USA, Brazil, and India formed a cluster, and the other 59 countries formed a cluster. Because these three countries in Cluster 2 have been at their peak since the beginning of the outbreak, the cluster analysis has affected the result. When we look at the variable values of the three countries, especially in terms of total cases, deaths and case fatality rates, and when we examine these variables in terms of their relationship to each other, they are quite similar, which allowed them to be in the same cluster.

In Cluster 1, where Turkey is located, we see that there are more countries that have managed to control themselves since the beginning of the epidemic. Also, the similarity of the countries in Cluster 1, in which Turkey is located, especially in terms of the variables of total cases, deaths, and case death rates, caused them to be included in the same cluster.

Finally, the IFCM clustering algorithm is known to be based on the traditional FCM algorithm by adding intuitionistic features to membership and objective functions. The fuzziness level is minimized when a total of 62 countries are divided into two clusters with an accuracy rate of 95.2% using the IFCM clustering algorithm [32]. As a result of the analyzed characteristics, the countries are classified into two clusters: 59 countries in Cluster 1, and the remaining countries in Cluster 2. When the resulting group structures are examined, it is determined that Group 2 has a more decisive grouping than Group 1.

5. CONCLUSION

It is critical to investigate the relationships between the distributions of the spread of this virus in other countries in order to pay attention to COVID-19 management policies and plans. The distributions of COVID-19 spread in high-risk countries were compared and clustered in this study using the IFCM clustering technique. For example, COVID-19 data sets were compared and clustered using the IFCM clustering technique for countries such as Austria, Azerbaijan, Australia, Belgium, Bosnia and Herzegovina, China, Costa Rica, Canada, Czech, Cyprus, Cuba, Denmark, Ethiopia, Ecuador, Egypt, France, Greece, Germany, Finland, Hungary, Indonesia, Iceland, Iraq, Israel, Ireland, Italy, Iran, Kazakhstan, Kenya, Japan, Malaysia, Norway, Mexico, Maldives, New Zealand, Nigeria, Netherlands, Pakistan, Palestine, Philippines, Peru, Portugal, Poland, Russia, Romania, Qatar, Switzerland, Saudi Arabia, South Korea, Sweden, Slovakia, South Africa, Slovenia, Ukraine, United Kingdom, Spain, Vietnam Venezuela, Turkey, Brazil, India, United States. The IFCM clustering algorithm was first applied to the relationship between the spread of the COVID-19 pandemic in this study. Moreover, the relationship between the spread of COVID-19 and six variables was examined. The obtained results showed that there were effective and important differences between the cumulative confirmed cases, cumulative deaths, and other variables between the countries. And, the distribution of distribution in Brazil, the USA and India is roughly similar but differs from other countries. Also, a clustering accuracy of over 95% can be achieved, which can be considered good to describe and deal with vague and uncertain data for this study. Furthermore, the IFCM algorithm can consider uncertainty information, which is critical for the success of some clustering tasks. For the fortune studies, the authors recommend that researchers classify statistical models that include fuzzy regression and fuzzy time series analysis, as well as fuzzy neural networks that can be applied to COVID-19 datasets.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interests. There aren't any potential conflicts of interests that are directly or indirectly related to the research.

AUTHORSHIP CONTRIBUTIONS

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Nihal Ince and Sevil Senturk. All authors read and approved the final manuscript.

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