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Spatial and Temporal Spread of the COVID-19 Pandemic Using Self Organizing Neural Networks and a Fuzzy Fractal Approach

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Abstract: In this article, the evolution in both space and time of the COVID-19 pandemic is studied by utilizing a neural network with a self-organizing nature for the spatial analysis of data, and a fuzzy fractal method for capturing the temporal trends of the time series of the countries considered in this study. Self-organizing neural networks possess the capability to cluster countries in the space domain based on their similar characteristics, with respect to their COVID-19 cases. This form enables the finding of countries that have a similar behavior, and thus can benefit from utilizing the same methods in fighting the virus propagation. In order to validate the approach, publicly available datasets of COVID-19 cases worldwide have been used. In addition, a fuzzy fractal approach is utilized for the temporal analysis of the time series of the countries considered in this study. Then, a hybrid combination, using fuzzy rules, of both the self-organizing maps and the fuzzy fractal approach is proposed for efficient coronavirus disease 2019 (COVID-19) forecasting of the countries. Relevant conclusions have emerged from this study that may be of great help in putting forward the best possible strategies in fighting the virus pandemic. Many of the existing works concerned with COVID-19 look at the problem mostly from a temporal viewpoint, which is of course relevant, but we strongly believe that the combination of both aspects of the problem is relevant for improving the forecasting ability. The main idea of this article is combining neural networks with a self-organizing nature for clustering countries with a high similarity and the fuzzy fractal approach for being able to forecast the times series. Simulation results of COVID-19 data from countries around the world show the ability of the proposed approach to first spatially cluster the countries and then to accurately predict in time the COVID-19 data for different countries with a fuzzy fractal approach.

Keywords: coronavirus; spatial similarity; fractal theory; neural networks; fuzzy logic

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1. Introduction

Recently, beginning at the end of 2019, during 2020 and now in 2021, we have experienced the rapid propagation of a novel coronavirus that killed more than eighteen hundred and infected thousands of individuals in just the first two months of the pandemic [1]. More recently, the virus has rapidly spread and has moved to many cities in all continents of the world. The most notable symptoms of the patients (based on experimental clinical data) are a dry cough, dyspnea, high fever and other related symptoms. At the beginning, most cases were localized to the city of Wuhan in China. As a consequence of this, in 30 January 2020, the World Health Organization (WHO) officially declared the COVID-19 outbreak to be a Public Health Emergency of International Concern [2].

Nowadays, due to the importance of the problem, many research groups in the world have dedicated their efforts to understanding all facets of the COVID-19 pandemic, and as a representative sample of the current literature in this area we mention some of these works. There was an interesting work on identifying emerging patterns that may contribute to achieving the automatic diagnosis of COVID-19 using convolutional neural networks, and the results showed that the method can provide a relevant impact on the automatic diagnosis of COVID-19 [3]. Another relevant work was the research of COVID-19 cases in China based on a dynamic statistical approach [4]. Other important articles can also be mentioned: a prediction with deep neural learning models of commercially available antiviral drugs that have a high probability of a positive impact on the novel coronavirus [5] and an early prediction of the COVID-19 outbreak in China based on a particular design of a mathematical model [6]. Additionally, the work presented in [7] described a range of practical online/mobile geographical information systems, mapping dashboards and applications for tracking the COVID-19 pandemic as it evolves around the globe. In addition, in [8], a proposal for utilizing the definition of cartograms in order to better visualize the spread of COVID-19 was presented. Finally, we can outline some recent studies that have been undertaken using artificial intelligence (AI); for example, the work presented in [9], in which the authors put forward the idea of using learning methods for improving the identification of COVID-19 cases in a quicker fashion when using a mobile phone-based web survey. In addition, AI techniques have been successfully utilized in decision-making problems for healthcare applications. This implies that AI-driven methods can be useful in identifying when COVID-19 outbreaks will occur, as well as in predicting their nature of spread rate around the globe [10].

However, the existing mentioned works have mostly treated the temporal facet of the problem, meaning that most of these contributions have been aimed at predicting or forecasting the COVID-19 data in a variety of ways. This facet is also relevant, as organizations need to estimate the number of COVID-19 cases to be able to produce the optimal decisions concerning the financial support to be directed to the solution of the COVID-19 problem. Therefore, the current gap in the existing knowledge is the lack of proposed models that can intelligently combine both the spatial and temporal aspects of the dynamics of COVID-19. In this sense, one of the most important contributions of this article is the utilization of neural networks for clustering similar countries, with respect to their status in the COVID-19 pandemic, and consequently the ability to put forward common strategies for countries in the same cluster. In addition, another important contribution is the use of the fuzzy fractal approach for efficiently predicting in each of the classes formed by the neural network. In our opinion, these contributions are both very important, including when combined, as they complement each other. This way, the temporal view of the problem is complemented by the spatial aspect in order to arrive at the global problem solution. In addition, we want to emphasize that the proposed approach is a combination of three methods, which has not previously been carried out in the literature (in this case, self-organized maps, fuzzy logic and fractal methods) for the spatial and temporal analysis of data and its application for the time series prediction.

Regarding the relevance of the paper to the sustainability area, the proposed approach is directly related to the healthcare theme. However, speaking more in general, this study proposes a novel methodology that can be used to monitor and stop the spread of COVID-19, which is a major public concern across the world. Therefore, this study certainly contributes to the social sustainability dimension.

The rest of the article is as follows. In Section 2, we briefly summarize the most important concepts of a special kind of neural network of an unsupervised nature. Section 3 explains the theoretical basis of the fractal dimension concept. Section 4 briefly describes the basic concepts of fuzzy logic and its application in a time series prediction. Section 5 offers a description of the problem to be solved and the method that is proposed in this work. Section 6 outlines the experiments and summarizes the results achieved with the proposal in this article. Section 7 offers a discussion of the obtained results. Lastly, Section 8 summarizes the conclusions that were elaborated after finishing this work.

2. Self-Organizing Neural Networks

The Kohonen map, which is also recognized as the self-organizing map (SOM), is a type of unsupervised neural network model that can be utilized to find and analyze patterns in datasets of high dimensionality. This neural network was originally put forward in 1982 by the Finnish Teuvo Kohonen. The SOM is a grouping method that finds clusters in a dataset and does not require the utilization of statistical methods. The SOM is composed of only two layers: the input and the output layers [11]. The main aim of this method is to move the input elements, having n attributes, to the output in a form where the elements have a relation among them (this is achieved by forming the clusters). In this model, connection weights are used so that the neurons have a relation between them and the inputs are directly connected to the outputs. The weights from the N inputs to the M output nodes are initialized with small values in a random fashion [12]. The activations of the output units based on this model are presented in Equation (1). The method for adapting the weights can be defined by Equation (2).

$$O_j = F_{min} d_j = F_{min}\left(\sum_i \left(X_i - W_{ij}\right)^2\right) \tag{1}$$

$$\Delta W_i j = O_j \eta \left(X_i - W_{ij}\right) \tag{2}$$

where O_j = activation of output unit j, X_i = activation value of input unit, W_{ji} = weights of lateral connections to the output, d_j = neurons in neighborhood, F_{min} = unity function giving a value of 1 or 0 and η = gain term that has a decreasing (in time) behavior. The ability to learn "competitively" is provided by the lateral connections, which can be viewed as the output layer neurons competing to be able to classify the input patterns. In the initial phase of training, the input patterns are offered to the neural model and the winner output is the one with the closest vector of weights and viewed as the cluster representative. Equation (1) illustrates how the distance is applied to make the selection of the winning neuron [13]. In Figure 1, an illustration of the self-organizing network architecture showing the neighborhood around the winner neuron is presented. It has a very simple structure without hidden layers, using only an input and an output layer. For the application in this paper, both the input and output layers have 199 nodes (this is the number of countries considered in the study) and the number of epochs is 1000.

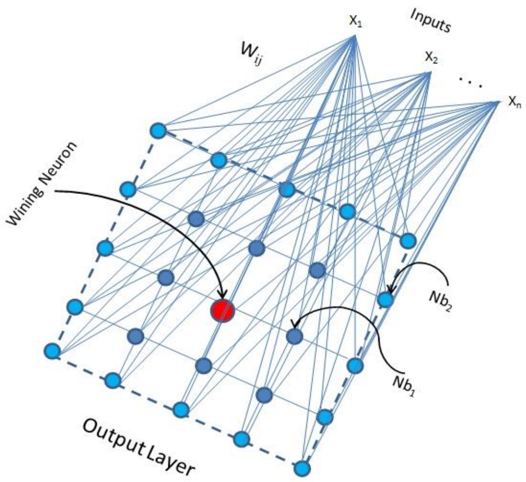

Figure 1. Example of the self-organizing neural network architecture.

Neural networks, such as the SOM model, have been widely applied in real-world problems, such as in identifying salinity sources [14], determining plant communities based on bryophytes [15] and the diagnosis of arthritis [16]. However, in this article, the neural network is utilized for classifying 199 countries of the globe with COVID-19 confirmed cases. The world dataset was obtained from the Humanitarian Data Exchange (HDX) [17].

3. Theoretical Background on the Fractal Dimension

Recently, significant advances have been achieved in the study of fractal theory constructs for understanding the geometrical complexity of objects [18]. As an example, time series coming from financial and economic dynamic systems can exhibit a fractal structure [19,20]. In addition, the fractal theoretical constructs have found remarkable applications in a plethora of areas, such as in medicine, manufacture, aerospace and control. A well-known definition of the dimension is:

$$d = \lim_{r \to 0} [\ln N(r)]/[\ln(1/r)] \tag{3}$$

where N(r) represents the number of boxes needed to cover a particular object and r represents a box size estimation. An approximation of the numeric value of the fractal dimension can be found by looking for the number of boxes covering the object for different r values (size of the box) and then computing a least squares regression in order to approximate the d value; this is known as the box counting algorithm. In Figure 2, an illustration of this algorithm for an arbitrary C curve is presented. In this case, for different r values we have a different number of boxes; then, evaluating a regression, a value of the box dimension can be found by Equation (4):

$$\ln N(r) = \ln\beta - d \ln r \tag{4}$$

where d represents the estimation of the fractal dimension, and the least squares method can approximate this value based on a given dataset.

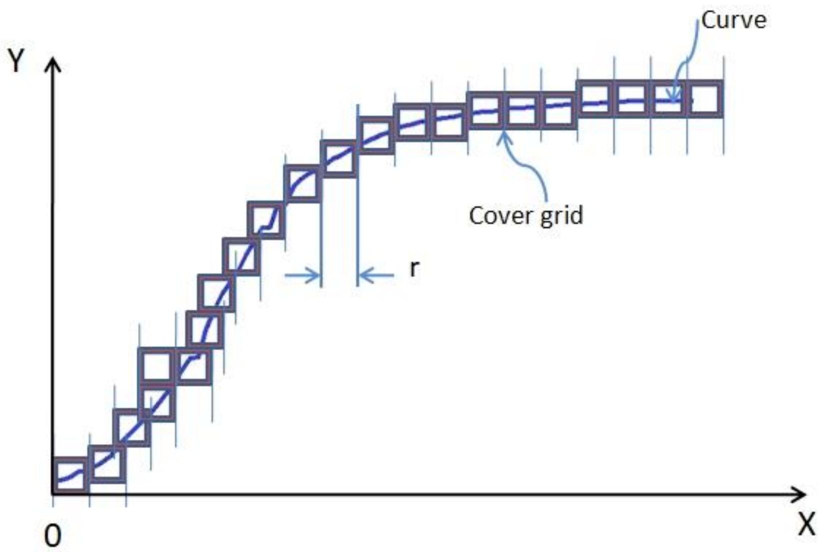

Figure 2. Illustration of the algorithm for a general curve C.

For the particular situation of this paper, classification of a time series can be achieved using the fractal dimension (the value of d is between 1 and 2, due to the fact that data are on the plane). The idea that is fundamental to this classification method is that the value of a smoother object's dimension is near to one. However, for a rougher object, the value of the dimension is near a value of two.

4. Basic Concepts of Fuzzy Logic for Forecasting

It is possible to utilize a fuzzy rule base as a forecasting model; for this, a suitable partition of the input space has to be made. In this case, the partition is needed to be able to discriminate among different objects by their features. To simplify the analysis, without losing generality, the objects are assumed to be on the plane, which in this particular situation are time series graphs. In this case, fuzzy clustering techniques [21,22] can be used to start grouping the data, and then after the clusters are formed, a fuzzy rule base can be constructed that basically constitutes a forecasting scheme for a particular application.

If we suppose that there are n objects O1, O2, . . . , On, then the fuzzy clustering algorithms may be utilized to find n pairs (Xi, Yi) i = 1, . . . , n, that correspond to the n cluster centers. In this form, a fuzzy system can be directly defined in a straightforward fashion:

$$\begin{array}{c} \text{If X is } x_1 \text{ and Y is } y_1 \text{ then Object is } O_1 \\ \text{If X is } x_2 \text{ and Y is } y_2 \text{ then Object is } O_2 \\ \ldots\ \ldots\ \ldots \\ \text{If X is } x_n \text{ and Y is } y_n \text{ then Object is } O_n \end{array} \tag{5}$$

This general scheme of fuzzy rules can be utilized for pattern recognition, or in the time series prediction, because both situations are structurally similar. These rules are in the Mamdani form [20] but can also be expressed as a Sugeno fuzzy model [22]. For high dimensionality cases, this approach can be extended in a direct form. However, the most important issue is that there is an exponential explosion of rules. The complete description of the fuzzy system in Equation (5) requires defining the membership functions of the X and Y fuzzy variables and finding their optimal values for the parameters.

5. Proposed Method

The datasets used for all of the experiments were collected from the Humanitarian Data Exchange (HDX) [17], which includes worldwide data COVID-19 cases for the countries. In particular, we considered data from 22 January 2020 to 20 January 2021. The particular datasets that were considered in the experimentation carried out in this work are: time_series_covid19_confirmed_global, time_series_covid19_recovered_global and time_series_covid19_deaths_global. Accordingly, the datasets for the countries include the confirmed, recovered and deaths cases.

5.1. Self-Organizing Maps for Spatial Calssification

In Figure 3, we can find an illustration of a neural network being used for the grouping and classification of countries based on their specific COVID-19 data. We have to say that we did initially propose the use of self-organizing maps in [23] for clustering both countries of the world and states inside Mexico. However, in this work, as a continuation of the previous publication, we are now integrating this spatial (geographical) analysis to the temporal analysis, which is carried out based on a classification method proposed by us in [24] and also by using the advantage of fuzzy logic in managing the intrinsic uncertainty in predicting time series, as we outlined previously in [25].

We can appreciate from Figure 3 that the SOM neural network groups the countries together based on their similarities; in this case, with respect to COVID-19 cases, and assuming that there are four clusters, which are illustrated with colors: red, orange, yellow and green. The main idea in this grouping of countries is that the COVID-19 incidence is clustered into low (green), medium (yellow), high (orange) and very high (red). Of course, this plot should be for a particular period of time, but here the figure is only shown for illustrative purposes.

5.2. Fuzzy Fractal for Temporal Analysis

In this section, the problem of temporal analysis in time series is considered. We can assume that $y_1, y_2, \ldots, y_n$ is a general time series. If the main aim of a method is a time series prediction, first, a temporal analysis is required to find the periodicities and trends of the series. Secondly, we apply clustering to the time series, producing n objects O_1, $O_2, \ldots, O_n$, and a fuzzy system, as established in Section 4. In this case, now it can be considered that the complexity of $O_1, O_2, \ldots, O_n$ is expressed by their dimensions *dim* and the class obtained by the SOM network is *class*, with fuzzy sets $x_1, x_2, \ldots, x_n$, and $y_1, y_2, \ldots, y_n$, respectively. Then, the fuzzy system for the prediction can be stated in the following general fashion.

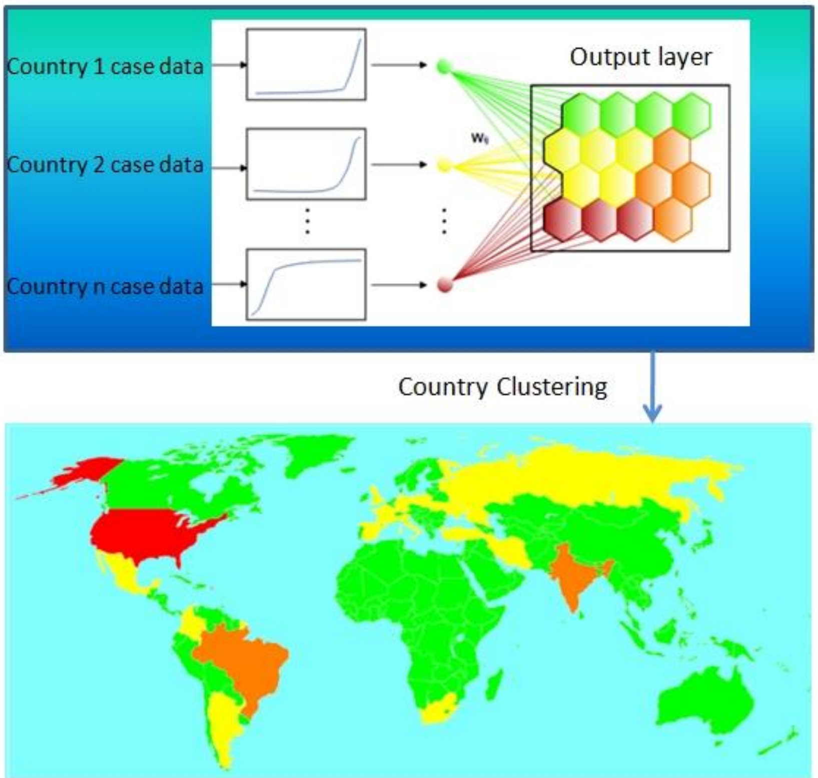

Figure 3. Illustration of a SOM neural network for country classification.

$$\begin{array}{c}\text{If } \mathit{dim} \text{ is } x_1 \text{ and } \mathit{class} \text{ is } y_1 \text{ then } \mathit{prediction} \text{ is } O_1 \\ \text{If } \mathit{dim} \text{ is } x_2 \text{ and } \mathit{class} \text{ is } y_2 \text{ then } \mathit{prediction} \text{ is } O_2 \\ \ldots \\ \text{If } \mathit{dim} \text{ is } x_n \text{ and } \mathit{class} \text{ is } y_n \text{ then } \mathit{prediction} \text{ is } O_n\end{array} \quad (6)$$

In this case, the membership functions for the *dim* variable, for the class of the country and for the geometrical objects need to be defined. The fuzzy rule base defined by Equation (6) can be implemented with a Mamdani reasoning scheme, and defuzzification by the centroid method. For the case of COVID-19 forecasting, two time series of interest were selected: confirmed cases and death cases. The main reasoning behind this decision is that both time series offer crucial information about the problem. Based on the previous discussion, a structure of two inputs and one output was selected for the fuzzy system. One input is the class of the country and the other input is the fractal dimension of confirmed cases or death cases, depending on which data we need to predict. Two fuzzy sets are used, low and high, to represent the corresponding values of the fractal dimensions. The output variable is the Increment on the Forecast of the Country (ΔP) with three fuzzy sets denoting the idea that countries can increment the forecast with three fuzzy degrees: high, medium and low. The overall idea is illustrated in Figure 4 as a block diagram, where we can note that the fractal dimension and the country class are entering the prediction module, and then the output is calculated, which is ΔP. Finally, this calculated increment should be added to the actual value (this is carried out in the Adder) in order to find the prediction of the following value of the time series, denoted as P_{n+1}.

The fuzzy rules were established by trial and error and based on the previous historical data and the respective calculated dimension values, in conjunction with expert knowledge on the subject. The architecture of the hybrid fuzzy fractal system is illustrated in Figure 5 in the form of a block diagram with both the inputs and the output. The set of fuzzy rules for achieving the classification is illustrated in Figure 6. The output membership functions are presented in Figure 7. In this case, we have one triangular and two trapezoidal functions. In Figure 8 the membership functions of the fractal dimension variable are illustrated. In this case, two Gaussian functions are used for the low and high values. In Figure 9, the functions of the class input variable are also illustrated.

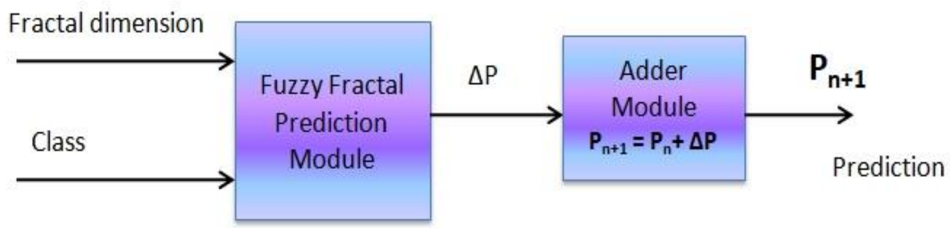

Figure 4. Architecture of the method for fuzzy fractal time series prediction.

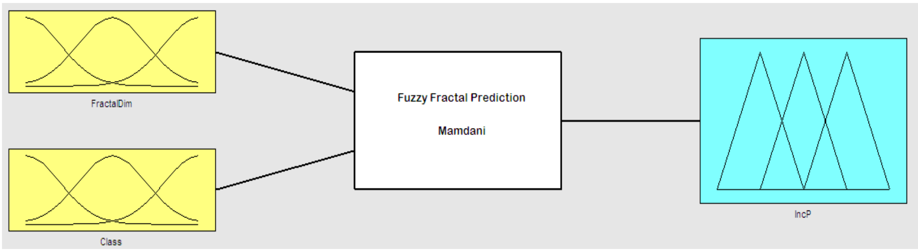

Figure 5. Fuzzy fractal system architecture for prediction of COVID-19 in the studied countries.

1. If (FractalDim is low) and (Class is low) then (IncP is Low) (1)
2. If (FractalDim is low) and (Class is medium) then (IncP is Midium) (1)
3. If (FractalDim is high) and (Class is high) then (IncP is High) (1)
4. If (FractalDim is high) and (Class is VeryHigh) then (IncP is VeryHigh) (1)

Figure 6. Fuzzy rules representing the forecasting knowledge in the system.

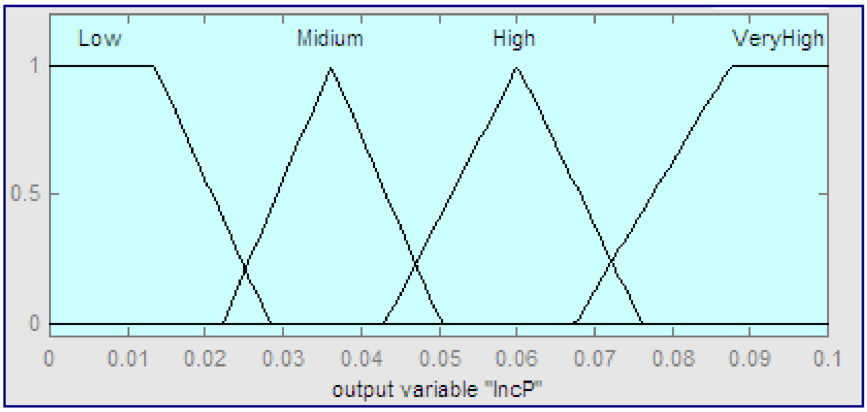

Figure 7. Output membership functions of the forecasting fuzzy system.

Finally, Figure 10 illustrates the fuzzy fractal model by using the nonlinear surface. This Figure illustrates the general nonlinear form of the fuzzy model with an overview of the complete model. We can appreciate a three-dimensional surface because we have two input and one output variables, which summarizes the relation between the variables in a general form.

5.3. Hybrid SOM Fuzzy Fractal Approach

In this section, the proposed hybrid approach, which combines self-organizing neural networks (for spatial analysis) and the fuzzy fractal method (for temporal analysis) in order to achieve the goal of obtaining a spatial–temporal model for time series forecasting, is presented. In Figure 11, the complete structure of the SOM fuzzy fractal approach is illustrated.

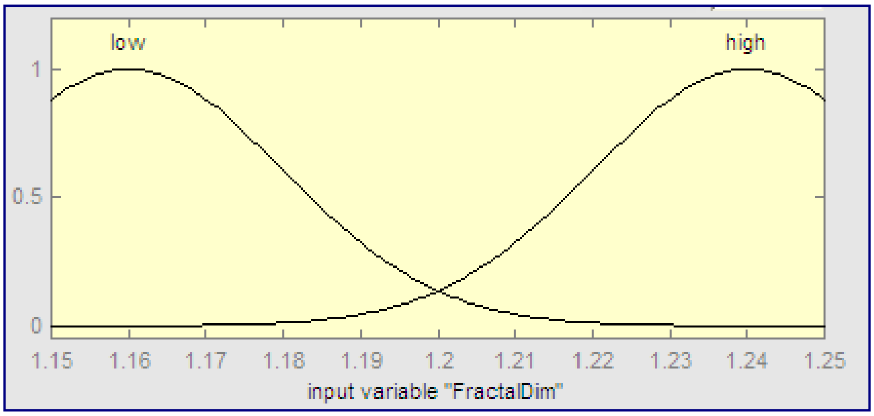

Figure 8. Input membership functions for the fractal dimension variable.

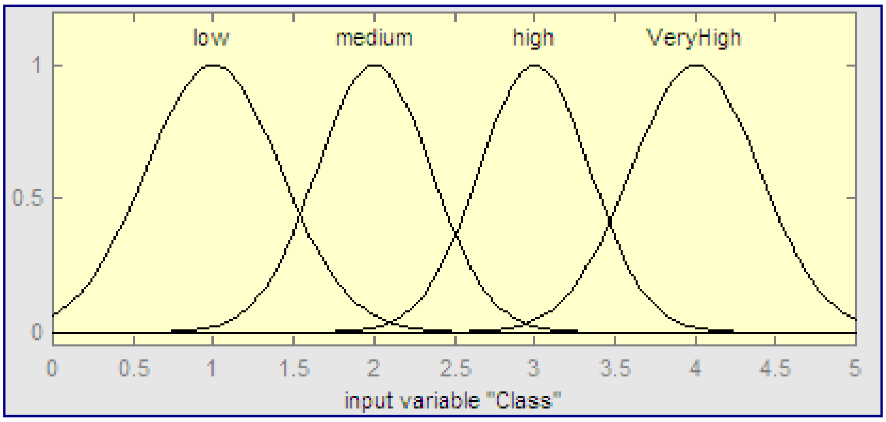

Figure 9. Output functions for the class linguistic variable.

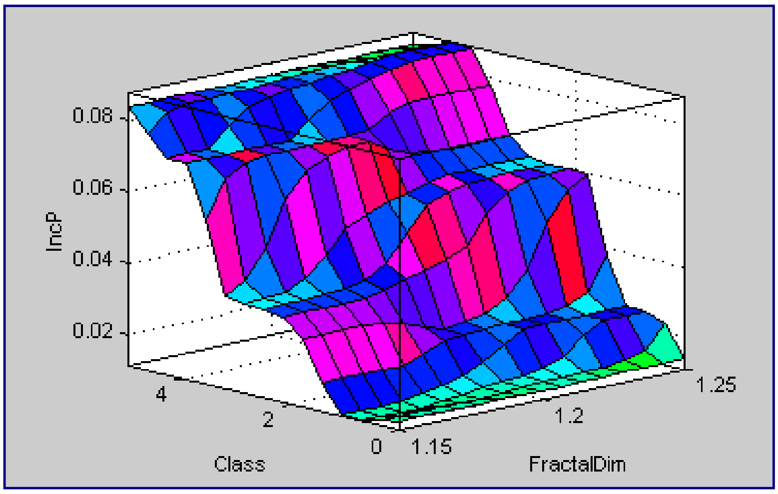

Figure 10. Nonlinear surface of the fuzzy fractal model.

The hybrid approach can be briefly described as follows. The COVID-19 data enters both the fractal dimension and the SOM modules, so that the numeric estimation of the fractal dimension and the clustering of the countries can be obtained. After these calculations are performed, both the numeric values of the dimension and the classes for the countries are used as inputs to the fuzzy fractal prediction module, which will in turn process the inputs to obtain the prediction. The fuzzy fractal module contains fuzzy rules that encapsulate the expert knowledge necessary to predict the time series utilizing the fuzzified values of the dimension and the class of the country.

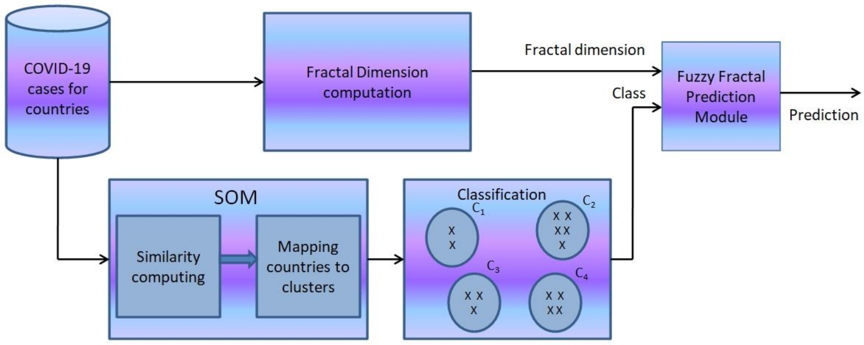

Figure 11. Complete structure of the SOM fuzzy fractal approach.

6. Simulation Results

The proposed approach based on unsupervised neural networks was applied in order to create clusters of countries in the globe. Based on these clusters, their classification was then performed by assuming four classes defined with respect to the emergency levels of COVID-19: very high, high, medium and low (indicated by red, orange, yellow and green colors, respectively). Table 1 indicates a list of the countries that are ordered according to the number of cases in the clusters, and after that, they are alphabetically ordered inside each cluster. The achieved results with this approach are presented in the following Figures. The details of the implementation of the proposed approach are as follows. The fractal dimension was calculated with Fractalyse 2.4.1 software. The SOM network and the fuzzy logic model were implemented in Matlab R2018b language. The hardware was a personal computer with Intel Core ™ i7—4510, 16 GB RAM and 2.60 GHz.

Table 1. Confirmed cases of COVID-19 around the globe (up to 20 January 2021).

Clustering	Country	Value
Very high	United States	28,336,097
High	Brazil	10,324,463
	India	11,046,914
Medium	Argentina	2,085,411
	Colombia	2,237,542
	France	3,721,061
	Germany	2,416,037
	Iran	1,598,875
	Italy	2,848,564
	Mexico	2,060,908
	Poland	1,661,109
	Russia	4,153,735
	South Africa	1,507,448
	Spain	3,170,644
	Turkey	2,665,194
	Ukraine	1,364,861
	United Kingdom	4,156,707
Low	Afghanistan	55,664
	Albania	103,327
	Algeria	112,461
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A plot of the clusters created with the neural network is presented in Figure 12, which clearly indicates the classes of COVID-19 confirmed cases for the period of time from 22 January 2020 to 20 January 2021.

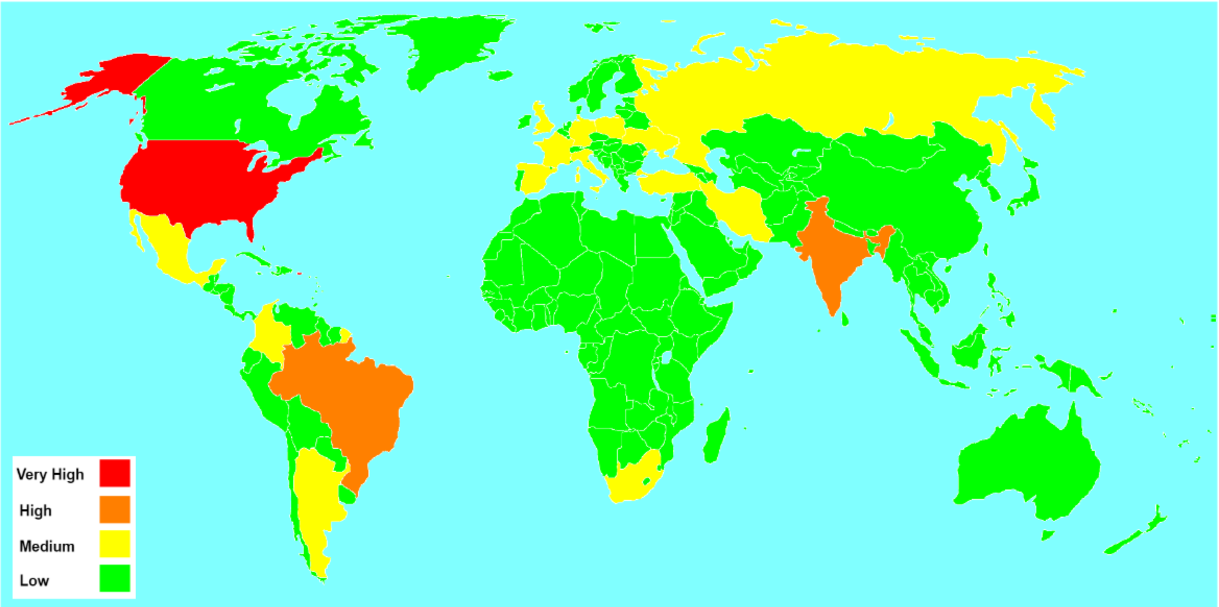

Figure 12. Classification of countries created with respect to confirmed COVID-19 cases.

A plot of the clusters of recovered cases created with the neural network is illustrated in Figure 13, which clearly indicates the classes for COVID-19 recovered cases for the period of time from 22 January 2020 to 20 January 2021.

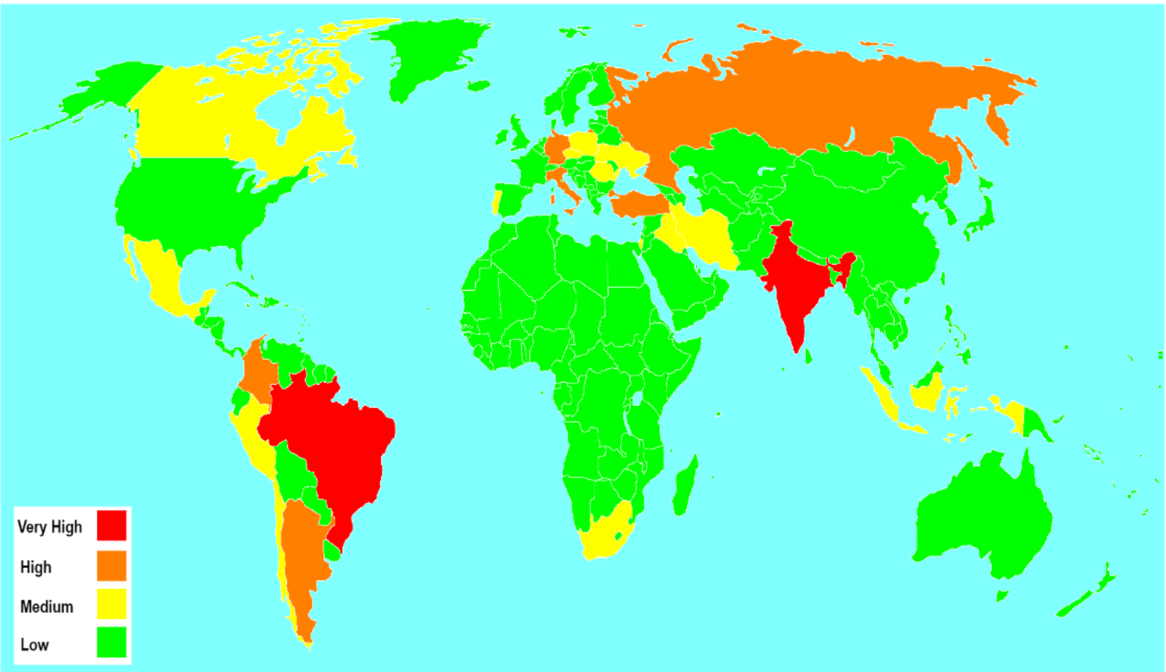

Figure 13. Classification of countries according to recovered COVID-19 cases.

In addition, an analogous analysis can also be made for the spatial analysis distribution of COVID-19 deaths around the globe. A plot of the groups created with the neural network is presented in Figure 14, which clearly indicates the COVID-19 classes for death cases for the period of time from 22 January 2020 to 20 January 2021. In Tables 2 and 3, we show the results for recovered and death cases, respectively.

The case of the time series prediction was used to illustrate that spatial classification helps to improve the prediction of the COVID-19 time series. The prediction approach is based on the temporal analysis information, and also uses the spatial information from the clustering that results from the neural network. In summary, we consider this spatial–temporal approach that combines the fuzzy fractal part with self-organizing neural network to be a good mixing or hybridization of methods to improve results. It is important to recall that the country class is not a fixed value, as it is dependent on the complexity evaluation for a specific time window. In this case, after the initial control actions in a next time window, the class value can decrease if the control action was the correct one. Based on preliminary experiments and analyses, we have recognized that in some situations with additional one-month data, we are able to recognize a change in the class of the country with the proposed method. In other cases, this could require larger periods of time, such as two to three months, for detecting a change. We consider that this is an interesting area of future work that we would like to investigate.

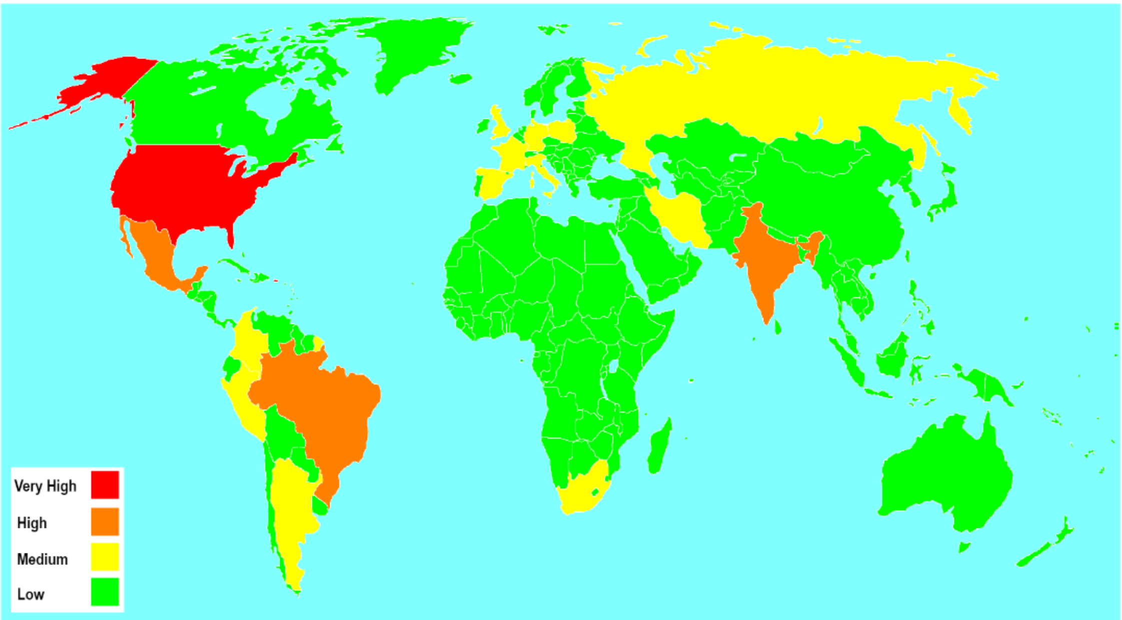

Figure 14. Classification of countries created with respect to death COVID-19 cases.

Table 2. Results for the clustering of COVID-19 recovered cases.

Clustering	Country	Value
Very high	Brazil	9,214,337
	India	10,738,501
High	Argentina	1,882,568
	Colombia	2,134,054
	Germany	2,231,073
	Italy	2,362,465
	Russia	3,709,938
	Turkey	2,540,293

Table 2. *Cont.*

Clustering	Country	Value
Medium	Canada	808,449
	Chile	767,332
	Czech Republic	1,037,430
	Indonesia	1,112,725
	Iran	1,365,253
	Iraq	625,447
	Israel	717,695
	Mexico	1,614,614
	Peru	1,196,515
	Poland	1,391,981
	Portugal	709,054
	Romania	731,049
	South Africa	1,422,622
	Ukraine	1,197,046
Low	Afghanistan	49,086
	Albania	66,309
	Algeria	77,537
	...	...

Table 3. Results for the clustering of COVID-19 death cases in the countries of the globe.

Clustering	Country	Value
Very high	United States	505,890
High	Brazil	249,957
	India	156,705
	Mexico	182,815
Medium	Argentina	51,650
	Colombia	59,260
	France	85,473
	Germany	69,170
	Iran	59,736
	Italy	96,666
	Peru	45,487
	Poland	42,808
	Russia	83,044
	South Africa	49,523
	Spain	68,468
	United Kingdom	121,979
Low	Afghanistan	2436
	Albania	1715
	Algeria	2970
	...	...

In a sequence of Figures, forecasting plots produced by the SOM fuzzy fractal approach for some countries for a period that is more recent are shown. In this case, forecasting 10 days ahead (21 January 2021 to 30 January 2021) based on data utilized for designing the fuzzy system (22 January 2020 to 20 April January 2021) is presented. Figure 15 illustrates forecasted confirmed cases in Belgium, where it is noticeable that the forecasted values are relatively near to the real values. Figure 16 illustrates forecasted confirmed cases in Italy. The percentage errors for Belgium and Italy are 0.24 and 0.05, respectively. In both cases, the forecasts are extremely near the real values, which confirms that the proposed approach appropriately deals with the time series prediction problem. Finally, we show for the same periods of time, in Figures 17 and 18, the forecasts for United States of America (USA), and Mexico, respectively. Again, the forecasts are very good, as the predicted values are very near to the real values. The percentage errors for USA and Mexico are 1.06 and 0.69, respectively.

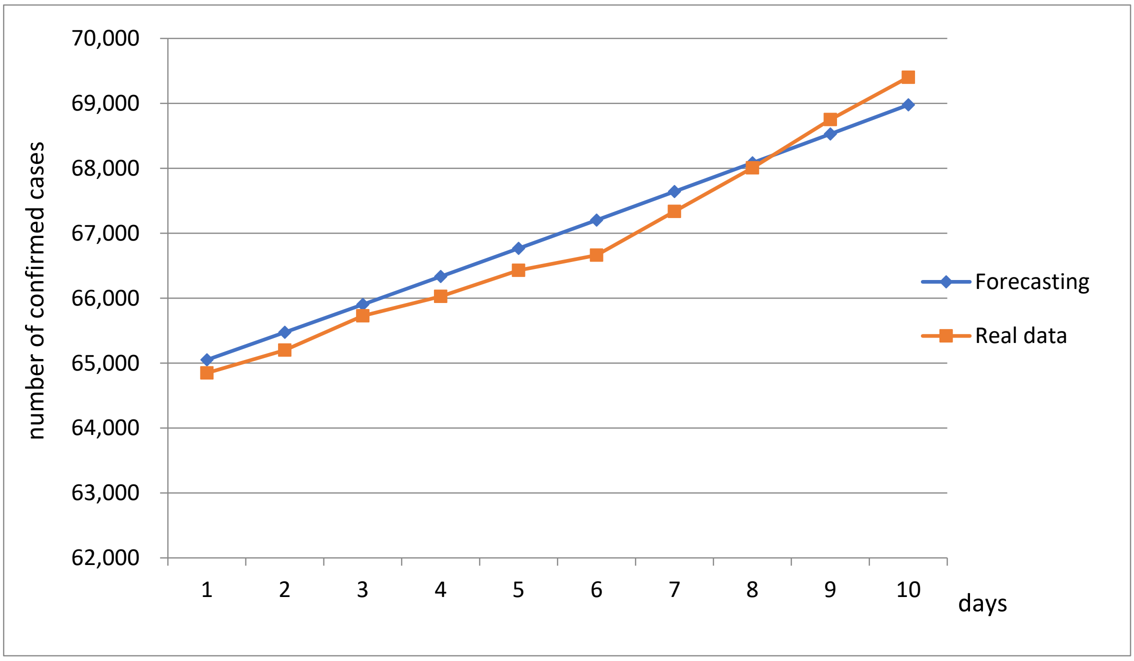

Figure 15. Forecasting of Belgium confirmed cases from 21 January to 30 January 2021.

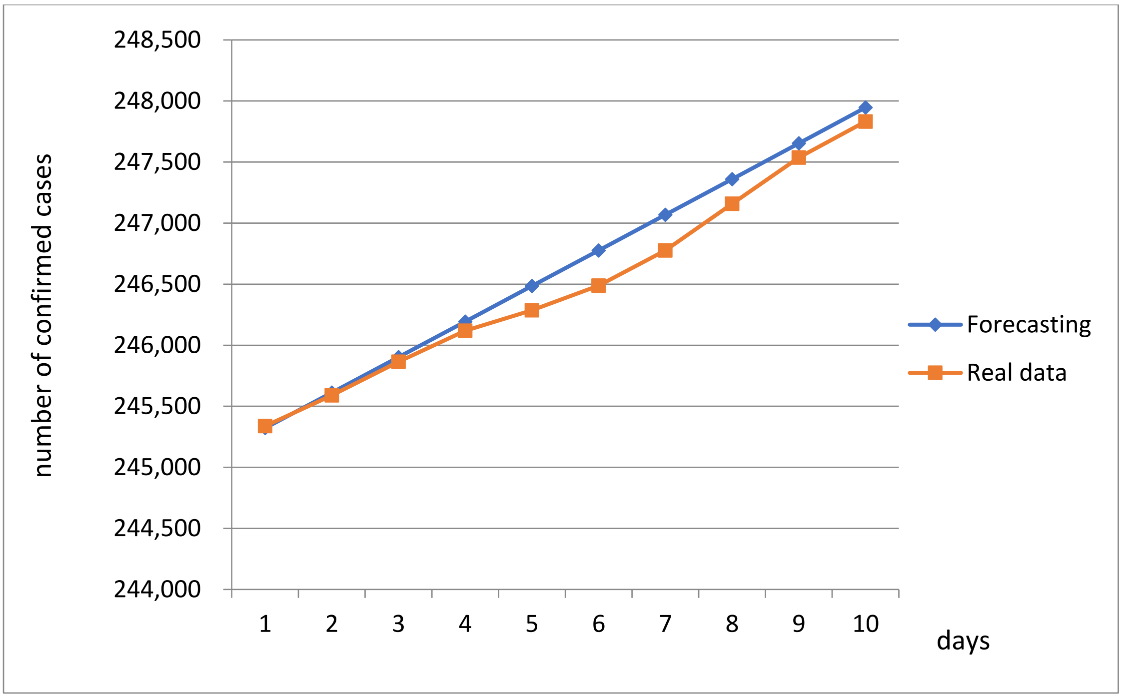

Figure 16. Forecasting of Italy confirmed cases (period of 21 January to 30 January 2021).

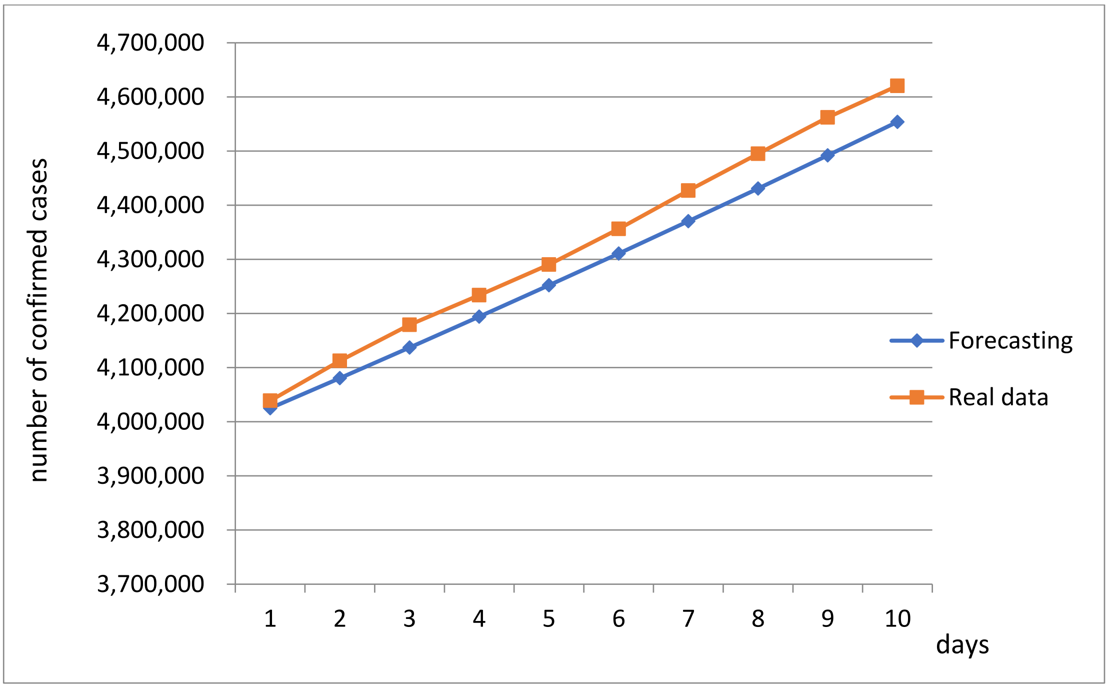

Figure 17. Forecasting COVID-19 cases in United States from 21 January to 30 January 2021.

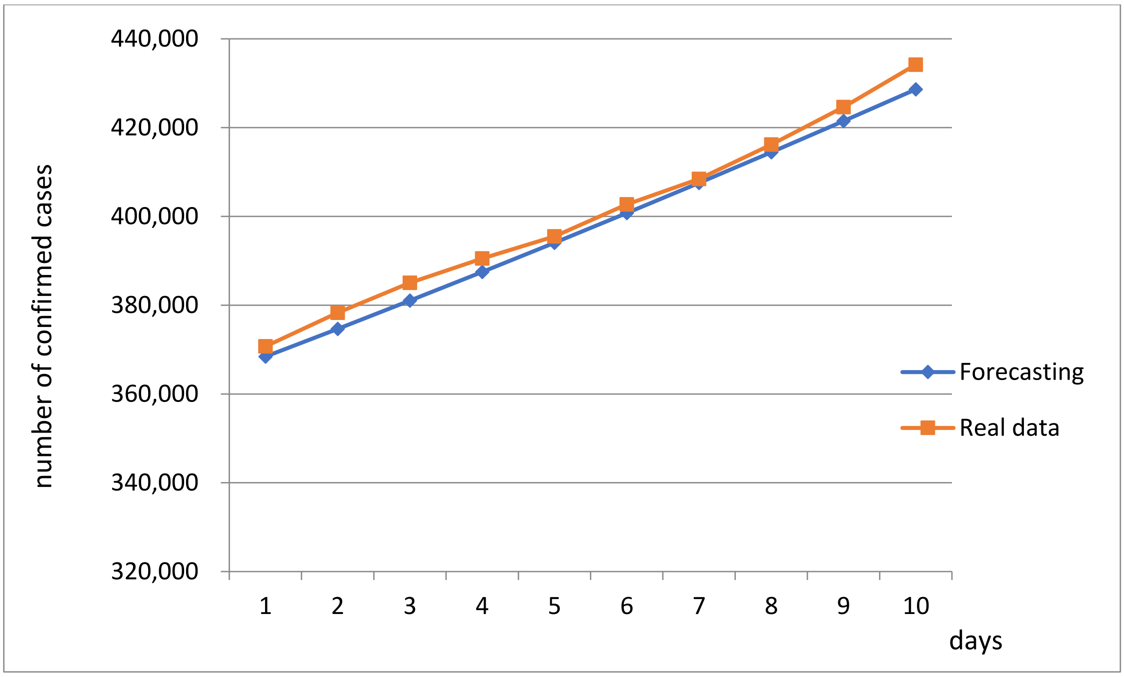

Figure 18. Forecasting COVID-19 confirmed cases in Mexico from 21 January to 30 January 2021.

In summary, the hybrid approach shows very good results and we plan to test with other periods of time and also with more countries.

7. Discussion of Results

In summary, we can state that based on the previous results, the proposed SOM fuzzy fractal approach performs positively, as it is able to predict the number of COVID-19 cases for the countries considered in the experiments. The prediction accuracy is not the same for all countries, but this was expected, as their dynamics are different. In considering similar works dealing with COVID-19 prediction [5,6], most of these papers are presenting prediction approaches based on mathematical models, which are very interesting, but mostly dependent on having very good mathematical models of the epidemic and then being able to mathematically derive equations for the prediction. On the other hand, the proposed approach in this article is mainly based on artificial intelligence techniques, such as fuzzy logic theory, that enable to directly represent expert knowledge on control by using fuzzy rules that form a fuzzy model. In this way, the fuzzy system does not depend on the mathematical model, but rather on an intelligent approach based on previous data (that are collected daily) and knowledge from human experts on the problem. In addition, in this fuzzy model, the fractal dimension is used to provide more information about the complexity of the dynamics of COVID-19 data, and thus helps to improve results. Finally, we have to say that in this work, the designs of the fuzzy rules and membership functions were achieved through trial and error in combination with knowledge about the problem, but we believe that the application of an optimization method can improve the results, and we will consider this task in our future work. We believe that metaheuristics coming from computational intelligence could be easily used to optimize the fuzzy model for prediction and further improve the results.

8. Conclusions

We have presented in this article a spatial and temporal study of the dynamics of the COVID-19 propagation by applying a special kind of neural network, which is the self-organizing map for the spatial analysis of data, and a fuzzy fractal system for modeling the temporal trends of COVID-19 data of the studied countries. Based on the self-organizing neural network, countries that have a similar COVID-19 propagation can be spatially grouped; in this fashion, we are able to analyze which countries have similar behavior and thus may benefit from using similar strategies in controlling the virus propagation. In addition, a fuzzy fractal approach is utilized for the temporal analysis of time series trends of the studied countries. Then, a hybrid combination of both the self-organizing maps and the fuzzy fractal system is proposed for the efficient forecasting of COVID-19 for the studied countries. Most of the previous articles concerning COVID-19 data have viewed the problem mostly regarding the temporal aspect, which is certainly important, but we believe that the combination of both aspects of the problem is relevant to improve the forecasting ability that is needed for real applications. In conclusion, the most relevant contribution of this article is the use of unsupervised neural networks for clustering similar countries and the fuzzy fractal approach for being able to forecast the times series and help in the fight against the COVID-19 pandemic, thus putting forward the idea that strategies for similar countries could be established accordingly with the proposed hybrid combination. If we view our contribution in a more general way, we can say that with our proposal we have filled the current gap in the existing knowledge, meaning the lack of models that combine both the spatial and temporal aspects of the dynamic systems; in particular, the existing lack of intelligent models that combine the temporal and spatial components of real problems, where fuzzy logic is used to perform this combination. Although the proposed model has been illustrated in this paper with the COVID-19 problem, we believe that the proposed model is applicable to other problems as long as they have both temporal and spatial components. We only need to have data from a problem that can be processed both by the self-organizing map and the fractal dimension algorithm, and then the proposed hybrid model can provide the prediction results. We envision that this proposed model can also be used in predicting economic or financial time series from countries, or similar problems. As future work, we may also consider applying other computational intelligent techniques (such as type-2 fuzzy logic, convolutional neural network, metaheuristic algorithms and swarm intelligence) that may help in dealing with this problem in a more convenient and improved way. We are also planning to develop a user-friendly software implementation of the proposed model that would require more detailed issues to be considered. Finally, we envision considering other novel approaches, as the ones outlined in [26,27], and other recent interesting works related to evolutionary or swarm fuzzy models and chaos, as in [28–31].

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