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Article

Spatial and Temporal Spread of the Coronavirus Pandemic using Self Organizing Neural Networks and a Fuzzy Fractal Approach

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Abstract: In this article, the evolution in space and in time of the coronavirus 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. Self-organizing neural networks possess the capability for clustering countries in the space domain based on their similar characteristics with respect to their coronavirus cases. In this form enabling finding the countries that are having similar behavior and thus can benefit from utilizing the same methods in fighting the virus propagation. To validate the approach, publicly available datasets of coronavirus cases worldwide have been used. In addition, a fuzzy fractal approach is utilized for the temporal analysis of time series of the countries. Then, a hybrid combination of both the self-organizing maps and the fuzzy fractal approach is proposed for efficient 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. A lot of the existing works concerned with the Coronavirus have look at the problem mostly from the temporal viewpoint that is of course relevant, but we strongly believe that the combination of both aspects of the problem is relevant to improve the forecasting ability. The most relevant contribution of this article is the proposal of combining neural networks with a self-organizing nature for clustering countries with high similarity and the fuzzy fractal approach for being able to forecast the times series and help in planning control actions for the Coronavirus pandemic.

Keywords: Coronavirus; Spatial Similarity; Fractal Theory; Neural Networks; Fuzzy Logic.

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 just in the first two months of the pandemic [1]. More recently, the virus has rapidly spread and has moved to many cities in all the continents of the world.

The most notable symptoms of the patients (based on experimental clinical data) are 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 January 30th of 2020, the World Health Organization (WHO) officially declared the COVID-19 Chinese outbreak to be a Public Health Emergency of International Concern [2].

Nowadays, due to the importance of the problem a lot of research groups in the world have dedicated their efforts to understanding all facets of the COVID-19 pandemics, and as a representative sample of the current literature in this area we mention some of these works. There is an interesting work on identifying emerging patterns that may contribute to achieving the automatic diagnosis of the COVID-19 using convolutional

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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 is the research of COVID-19 cases in China based on a dynamic statistical approach [4]. Other important articles can be also mentioned: the 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 the early prediction of the coronavirus outbreak in China based on a particular design of a mathematical model [6]. Also, the work presented in [7], describing a range of practical online/mobile geographical information systems and mapping dashboards and applications for tracking the coronavirus pandemic as they evolve around the globe. In addition, in [8] a proposal for utilizing the definition of cartograms to visualize, in a better way, 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. Also, 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 predict their nature of spread rate around the globe [10].

However, the existing mentioned contribution have mostly treated the temporal facet of the problem and this means that most of these contributions have been aimed at predicting or forecasting in a variety of ways the coronavirus data. This facet is also very relevant, as organizations need to estimate the number of coronavirus cases to be able to produce the optimal decisions concerning the financial support to be directed for the solution of the COVID-19 problem. However, it is our strong believe that the spatial facet of the problem is relevant, so 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 Coronavirus pandemic, and consequently be able to put forward common strategies for countries in the same cluster. In addition, 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 as also when combined as they complement each other. In this way the temporal view of the problem is complemented by the spatial aspect to arrive at the global problem solution.

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 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. Lastly, Section 7 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 kind 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 Finish 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 by 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 that the elements have a relation among them (this is done 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 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 Eq. 1. The method for adapting the weights can be defined by Eq. 2.

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

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

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, 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.

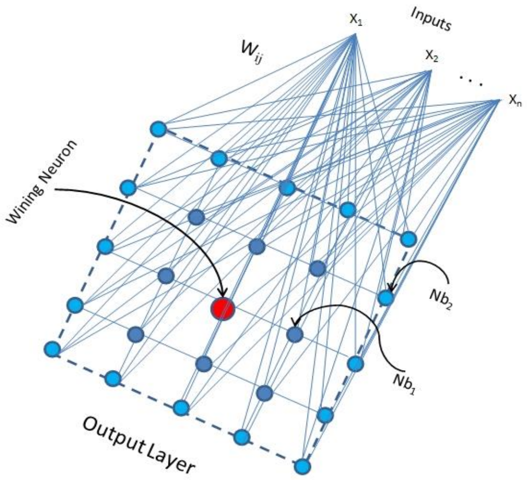

Figure 1 Example of the self-organizing neural network architecture

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

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

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:

$$d = \lim\, [\ln N(r)] / [\ln(1/r)] \quad (3)$$

$r \to 0$

where *N(r)* is representing the number of boxes needed to cover a particular object and r represents a box size estimation. An approximation to 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 to approximate the *d* value and 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 different number of boxes and 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 is representing the estimation of the fractal dimension, and the least squares method can approximate this value based on a given dataset.

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

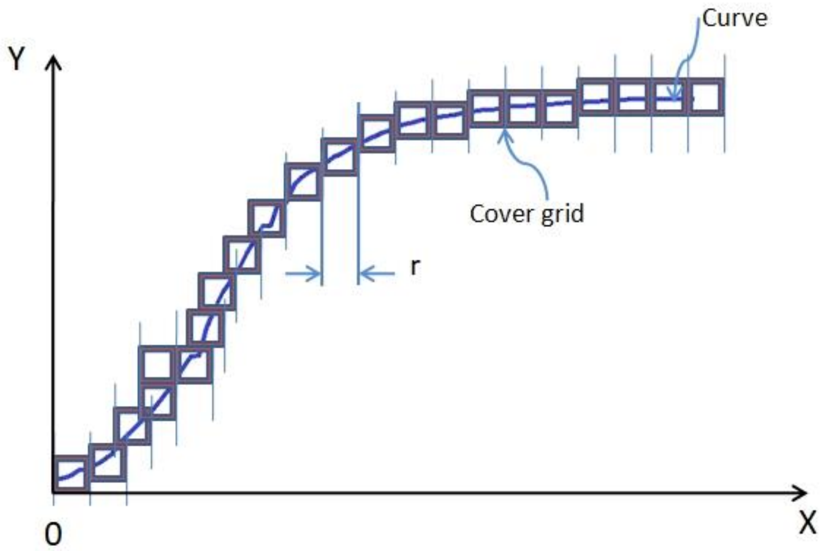

Figure 2 Illustration of the algorithm for a general curve C

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 constitute 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, which correspond to the *n* cluster centers. In this form, a fuzzy system can be directly defined in a straightforward fashion:

If X is x_1 and Y is y_1 then Object is O_1

If X is x_2 and Y is y_2 then Object is O_2 (5)

… … …

If X is x_n and Y is y_n then Object is O_n

This general scheme of fuzzy rules can be utilized for pattern recognition or in the time series prediction because in both situations is structurally similar. 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 (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 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 January 22, 2020 to January 20, 2021. The particular datasets that were considered in the experimentation done 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 grouping and classification of countries based on their specific COVID-19 data.

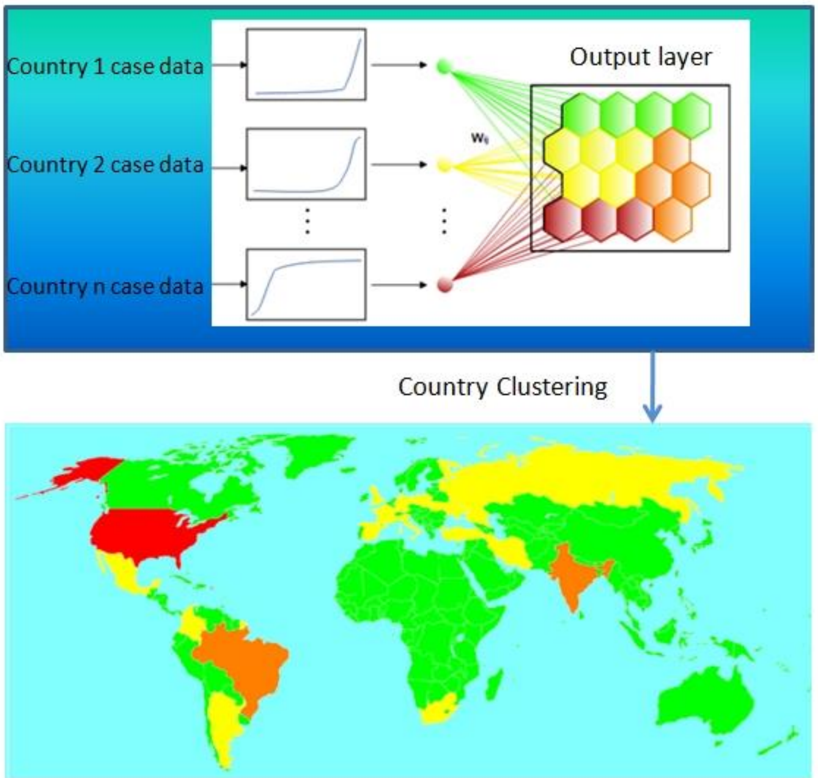

Figure 3 Illustration of a SOM neural network for country classification

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 4 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 purpose.

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 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 and this produces *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 prediction can be stated in the following general fashion.

If *dim* is x_1 and *class* is y_1 then *prediction* is O_1

If *dim* is x_2 and *class* is y_2 then *prediction* is O_2

… … … (6)

If *dim* is x_n and *class* is y_n then *prediction* is O_n

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 done in the Adder) to find the prediction of the following value of the time series, denoted as P_{n+1}.

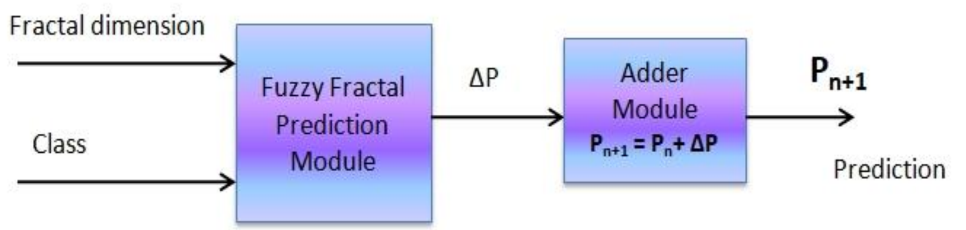

Figure 4 Architecture of the method for fuzzy fractal time series prediction

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 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.

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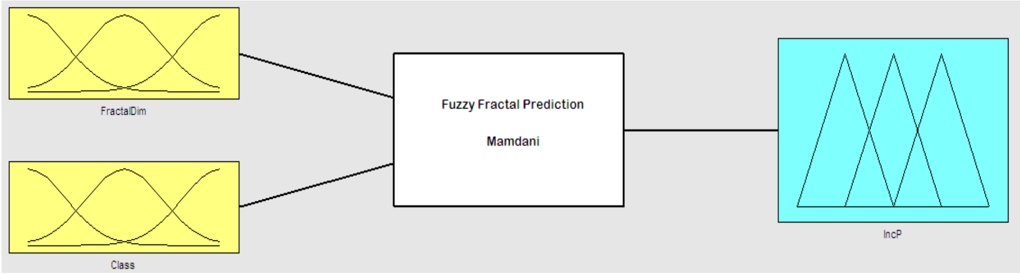

Figure 5 Fuzzy fractal system architecture for prediction of COVID-19 in the Countries

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

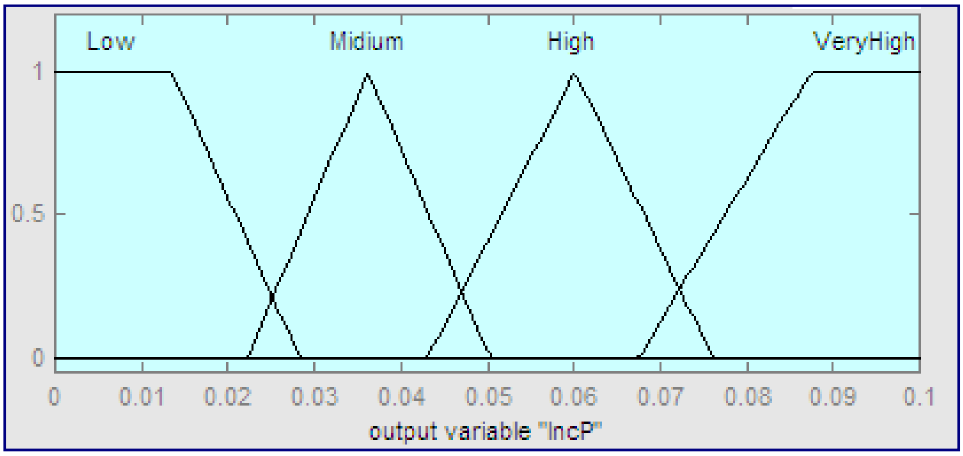

Figure 7 Output membership functions of the forecasting fuzzy system

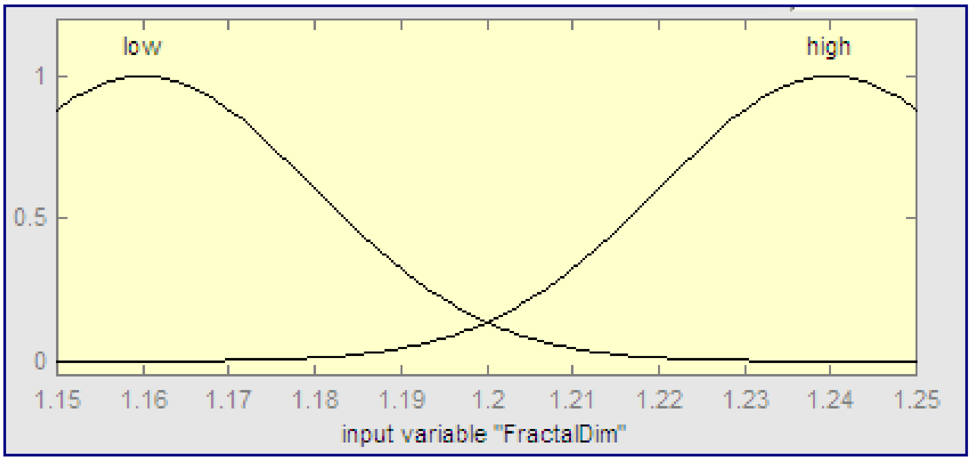

Figure 8 Input membership functions for the fractal dimension variable

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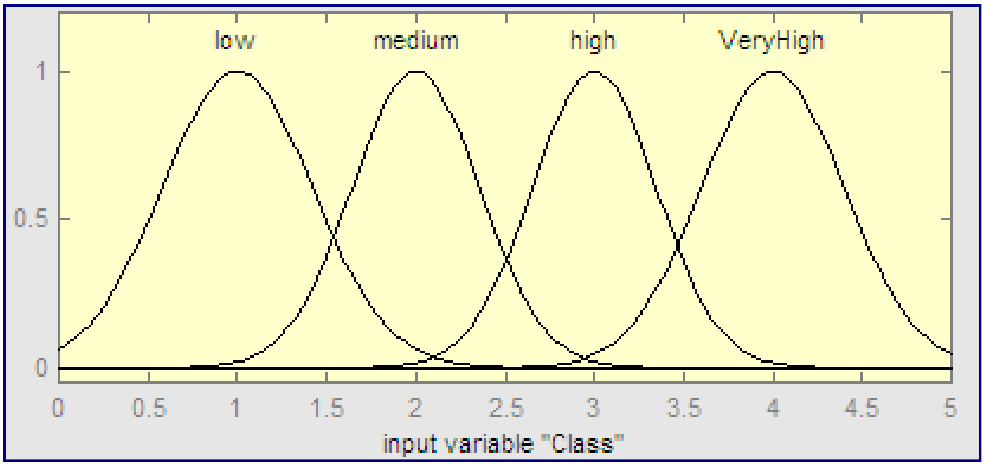

Figure 9 Output functions for the class linguistic variable

Finally, we are illustrating in Figure 10 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 in a general form the relation between the variables.

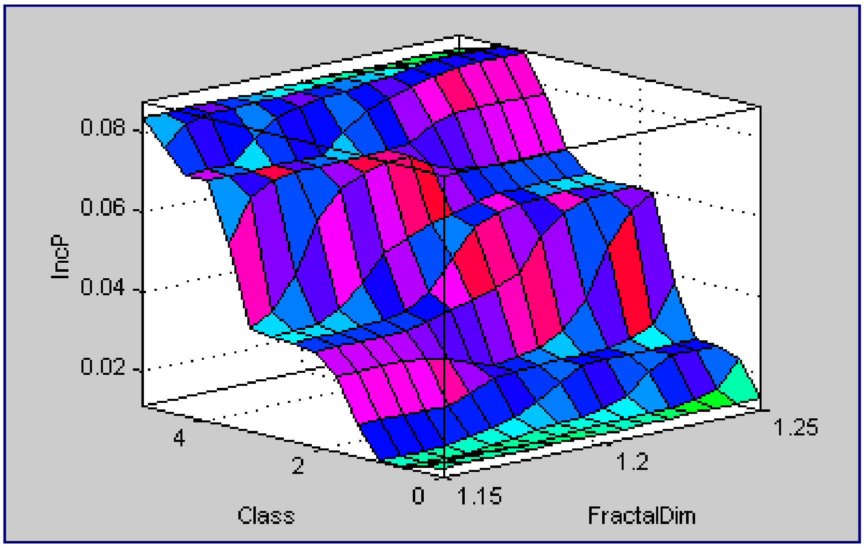

Figure 10 Nonlinear surface of the fuzzy fractal model

5.3. Hybrid SOM Fuzzy Fractal Approach

In this section the proposed hybrid approach combining self-organizing neural networks (for spatial analysis) and the fuzzy fractal method (for temporal analysis) 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.

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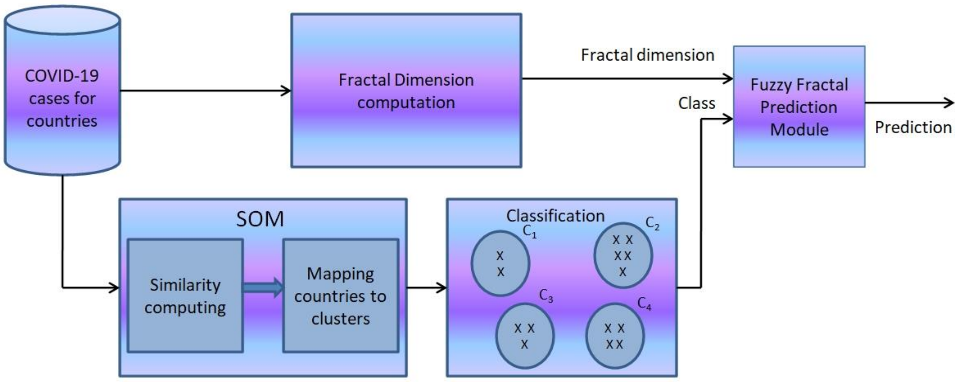

Figure 11 Complete structure of the SOM fuzzy fractal approach

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.

6. Simulation Results

The proposed approach based on unsupervised neural networks was applied to create clusters of countries in the globe. Based on these clusters, then their classification was performed by assuming 4 classes defined with respect to the emergency levels of Coronavirus: 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 alphabetically ordered inside each cluster. The achieved results with the approach are presented in the following Figures.

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 22-01-2020 to 20-01-2020.

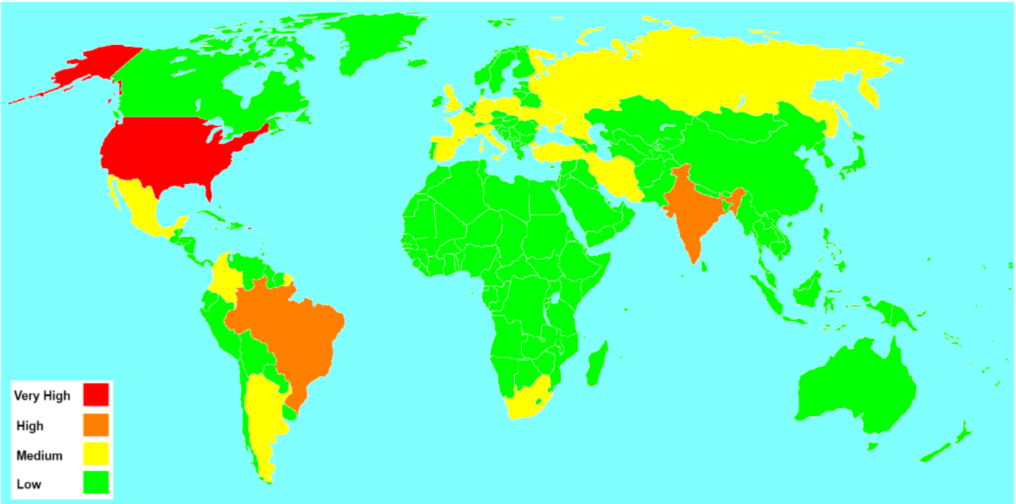

Figure 12 Classification of countries created with respect to confirmed Coronavirus cases

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 January 22 of 2020 to January 20 of 2021.

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

Clustering	Country	Value
Very high	United States	28336097
High	Brasil	10324463
	India	11046914
Medium	Argentina	2085411
	Colombia	2237542
	France	3721061
	Germany	2416037
	Iran	1598875
	Italy	2848564
	Mexico	2060908
	Poland	1661109
	Russia	4153735
	South Africa	1507448
	Spain	3170644
	Turkey	2665194
	Ukraine	1364861
	United Kingdom	4156707
Low	Afganistán	55664
	Albania	103327
	Algeria	112461
	…	…

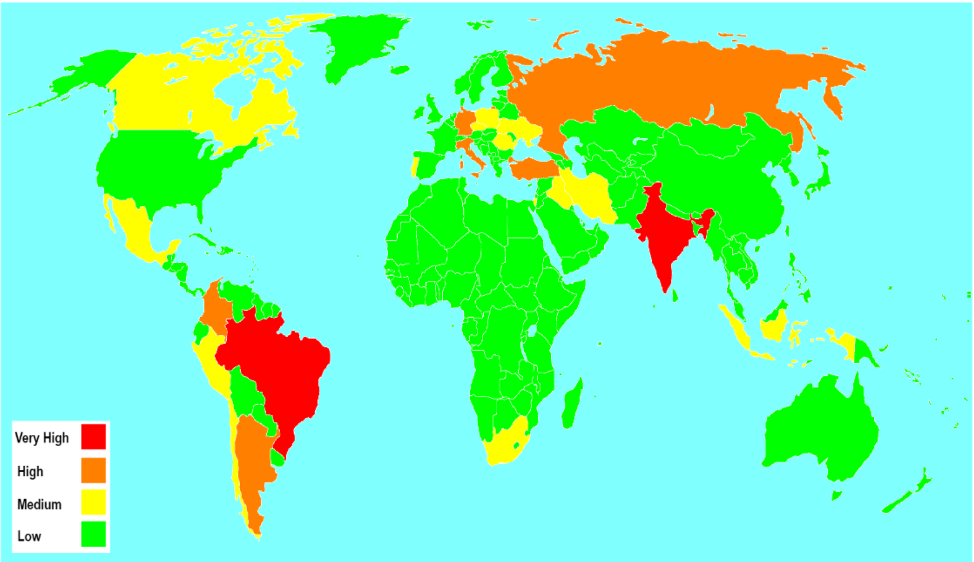

Figure 13 Classification of countries according to recovered Coronavirus cases

In addition, an analogous analysis can also be made for the spatial analysis distribution of Coronavirus 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 January 22 of 2020 to January 20 of 2021. In Tables 2 and 3 we show the results for recovered and death cases, respectively

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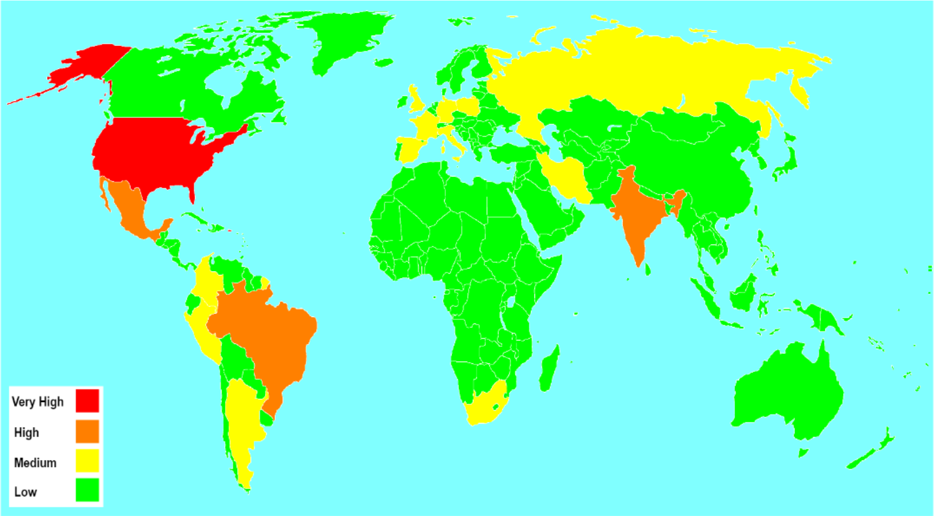

Figure 14 Classification of countries created with respect to death Coronavirus cases

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

Clustering	**Country**	**Value**
Very high	Brazil	9214337
	India	10738501
High	Argentina	1882568
	Colombia	2134054
	Germany	2231073
	Italy	2362465
	Russia	3709938
	Turkey	2540293
Medium	Canada	808449
	Chile	767332
	Czechia	1037430
	Indonesia	1112725
	Iran	1365253
	Iraq	625447
	Israel	717695
	Mexico	1614614
	Peru	1196515
	Poland	1391981
	Portugal	709054
	Romania	731049
	South Africa	1422622
	Ukraine	1197046
Low	Afghanistan	49086
	Albania	66309
	Algeria	77537
	…	…

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

Clustering	Country	Value
Very high	United States	505890
High	Brazil	249957
	India	156705
	Mexico	182815
Medium	Argentina	51650
	Colombia	59260
	France	85473
	Germany	69170
	Iran	59736
	Italy	96666
	Peru	45487
	Poland	42808
	Russia	83044
	South Africa	49523
	Spain	68468
	United Kingdom	121979
Low	Afganistán	2436
	Albania	1715
	Algeria	2970
	…	…

The case of time series prediction was used to illustrate that spatial classification helps improving the prediction of COVID-19 time series. The prediction approach is based on the temporal analysis information, and also uses the spatial information from the clustering resulting 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 analysis, we have recognized that in some situations with an 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, like 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.

In a sequence of Figures, we are showing forecasting plots produced by the SOM-fuzzy-fractal approach for some countries for a period that is more recent. In this case, forecasting 10 days ahead (January 21, 2021 to January 30, 2021) based on data utilized for designing the fuzzy system (January 22, 2020 to April January, 20, 2021) is presented. Figure 15 illustrates Belgium forecasted confirmed cases, where it is noticeable that forecasted values are relatively near to the real values. Figure 16 illustrates Italy forecasted confirmed cases. The percentage errors for Belgium and Italy are 0.24 and 0.05, respectively. In both cases, the forecasts are really near the real values, which confirms that the proposed approach appropriately deals with the time series prediction problem. Finally, we show for

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the same periods of time, in Figures 17 and 18, the forecasts for United States of America (USA), and Mexico, respectively. Again, 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.

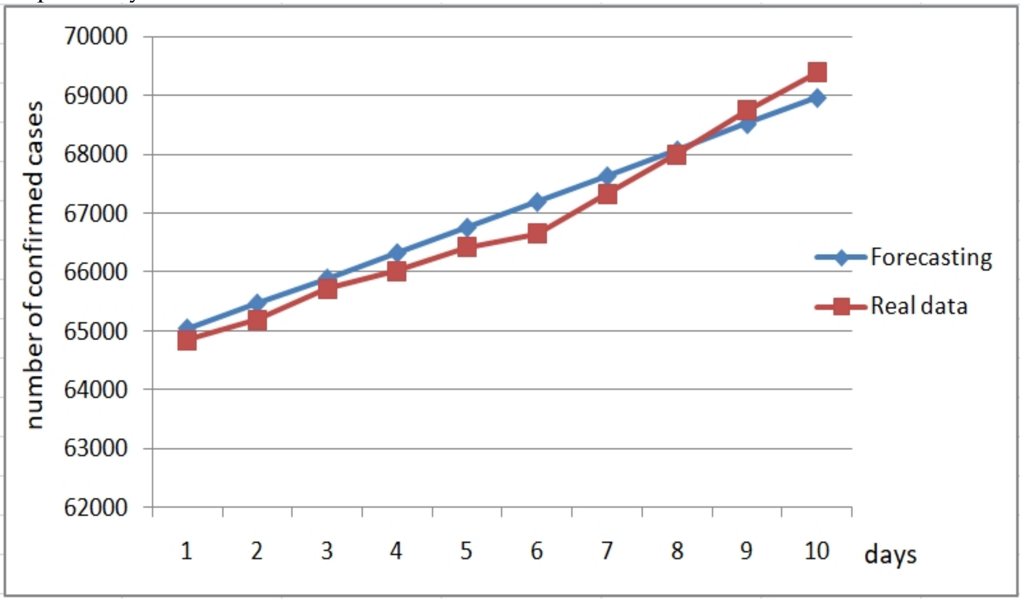

Figure 15 Forecasting of Belgium confirmed cases from 22 July to 1 August 2020

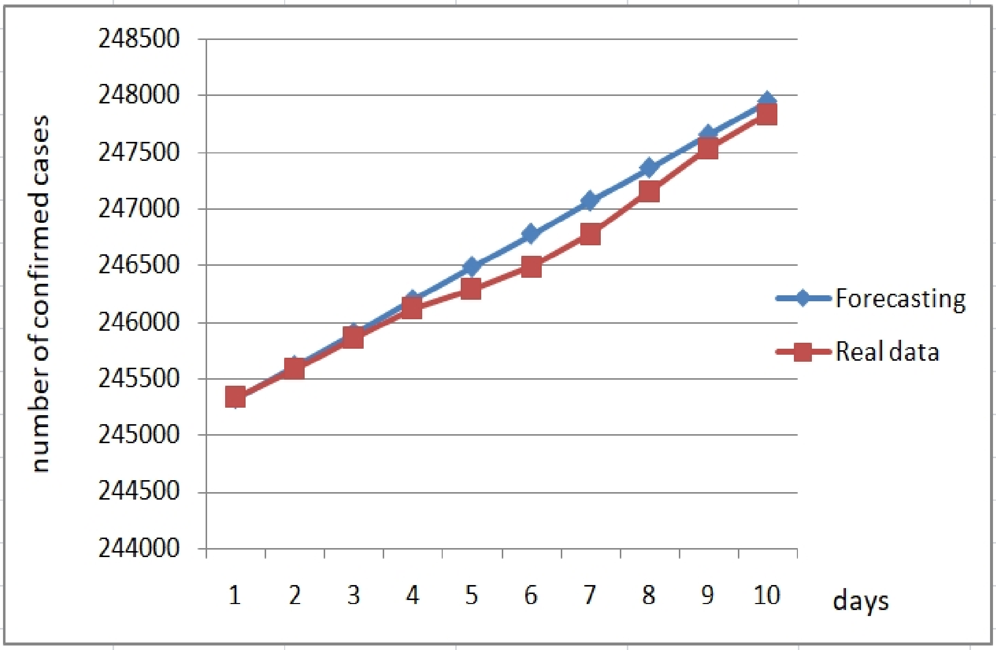

Figure 16 Forecasting of Italy confirmed cases (period of 22 July to 1 August of 2020)

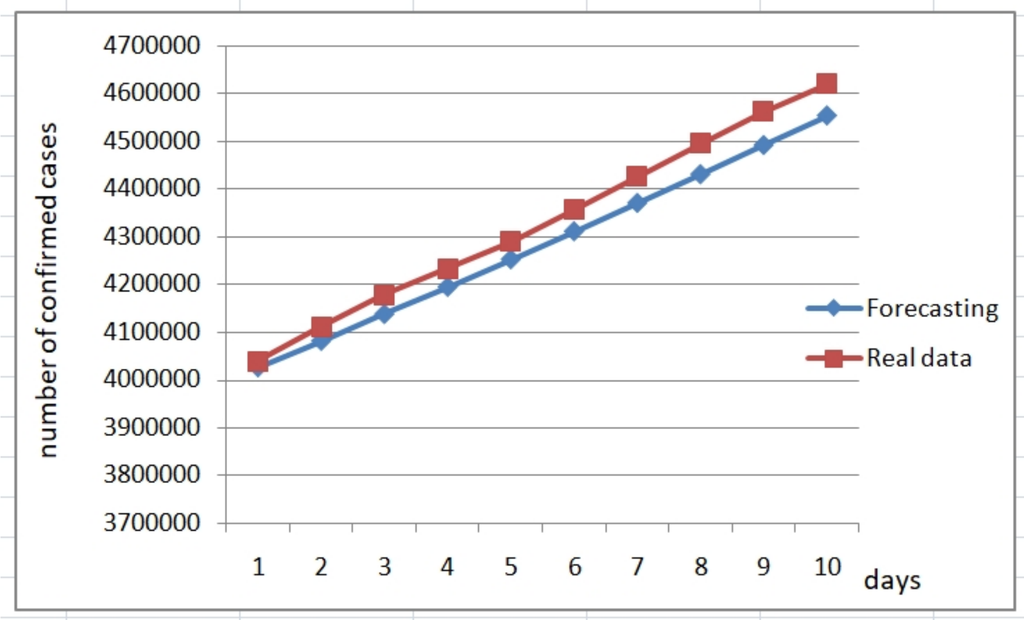

Figure 17 Forecasting COVID-19 cases in United States from 22 July to 1 August

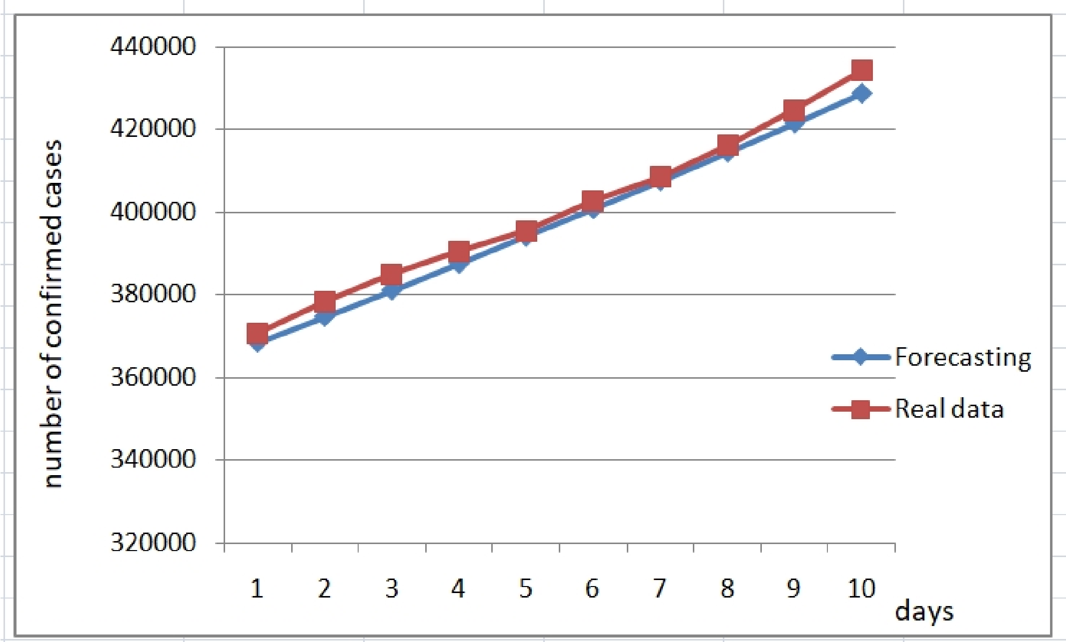

Figure 18 Forecasting COVID-19 confirmed cases in Mexico from 22 July to 1 August

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. Conclusions

We have presented in this article a spatial and temporal study of the dynamics of the coronavirus 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 countries. Based on the self-organizing neural network, countries that have a similar coronavirus propagation can be spatially grouped, in this fashion we can be able to analyze which countries are having 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 countries. Then, a hybrid combination of both the self-organizing maps and the fuzzy fractal system is proposed for efficient forecasting of COVID-19 for the countries. Most of the previous articles concerning Coronavirus data have viewed the problem mostly on temporal aspect, which for sure is 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 Coronavirus pandemic, and thus putting forward the idea that strategies for similar countries could be established accordingly with the hybrid combination here proposed. As future work, we may consider applying other computational intelligent techniques (like type-2 fuzzy logic, convolutional neural network, metaheuristic algorithms and swarm intelligence) that may help in dealing in a more convenient and improved way with this problem. Finally, we envision considering other novel approaches, as the ones outlined in [23, 24], and other recent interesting works related to evolutionary or swarm fuzzy models and chaos, as in [25-28].

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