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Best Practice Performance of COVID-19 in America continent with Artificial Intelligence

Hossein Komasi[1], Amir Karbassi Yazdi[2,*]

[1] School of Engineering, Catholic University of the North, Coquimbo 1780000, Chile
[2] Departamento de Ingenieria Industrial y de Sistemas,Facultad de Ingenieria,Universidad de Tarapaca , Arica, Chile

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ABSTRACT

Metaheuristics were employed with ANFIS and K-means to determine whether COVID-19 performed the best on the American continent. A few individuals lost their lives to COVID-19, and quite a few nations assisted with this matter. It is essential to know the nations that performed the best in COVID-19 management. Researchers can carry out evaluations of nations using metaheuristic approaches and ANFIS. Based on the performance of these nations, clusters will be determined and established. The research excluded only two of the thirteen criteria that were investigated. Seven distinct groups have been established for each of the thirty-five nations. In the United States, the performance regarding COVID-19 is the poorest, according to the research. These three nations also had the most extraordinary response to the COVID-19 outbreak. Based on the methodology and the context of the literature evaluation, this work's contribution may be divided into two distinct areas. The existence of research gaps makes it clear that a regional emphasis is needed rather than a focus on a nation or a portion of a country, which illustrates the requirement for a focus on the whole continent.

1. Introduction

A significant social, economic, and health problem arose at the beginning of 2020 with the worldwide pandemic that was the Coronavirus Disease 2019 (COVID-19), which was caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) [1]. Respiratory droplets transmit this highly contagious virus in direct touch with contaminated surfaces and, in rare instances, aerosols [2]. Rapid COVID-19 transmission and a wide spectrum of symptoms ranging from no symptoms to life-threatening respiratory illness necessitated an all-encompassing response spanning public health initiatives, clinical treatment, and vaccine development [3]. Several published reports indicate that the spread of COVID-19 is highly aggressive [4]. This is due to the uncertainty and complexity of the COVID-19 outbreak, as well as the random nature of its appearance in different countries [5]. Standard epidemiological models, such as susceptible-infected-resistant (SIR)-based models, have

* *Corresponding author.*
E-mail address: akarbassiy@academicos.uta.cl

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been challenged to deliver higher performance in individual countries [6]. COVID-19 has been the subject of many research studies, and more are coming; floods of massive data about it are continuously accumulating [7]. No precise prediction can be made regarding the transmission time or end of the pandemic. It is well known that various diseases are affected by weather factors, and temperature and relative humidity may also interact with the incidence of COVID-19[8]. Therefore, an early warning system for epidemics on a continental and global scale is necessary. The number of new coronavirus cases (COVID-19) occurring daily in different countries worldwide has increased [9]. As we approach the end of the year, COVID-19 remains an infectious pandemic that has frightened the world and continues to threaten the lives of billions of people worldwide [8]. It is vitally essential for medical practitioners to identify Coronaviruses (COVID-19) in their work. Unfortunately, the COVID-19 virus has spread so rapidly among people that it has now reached millions of people worldwide in just a few months. To avoid the spread of the pandemic, it is crucial to identify infected individuals as quickly and reliably as possible.

Though many countries have progressed beyond the early stages of the COVID-19 outbreak, much remains to be learned [10]. The way governments could be ready for future pandemics is covered in this research. Evaluating options could let nations be prepared for disaster [11]. The main goal of the research is to ensure that healthcare facilities have sufficient tools and coordinate successful legislative and regulatory-based epidemic prevention strategies. National and local lockdown policies must be controlled strictly. According to comprehensive research, machine learning may predict epidemic trends in high-risk areas. Pandemic data allows governments to develop thorough strategies and safeguard the people. Our current study aims to deploy machine learning approaches for clustering in several selected countries regarding the performance of COVID-19 in our current study.

As a result of this study, the following significant contributions have been made:

This study presents a machine-learning model for clustering American countries affected by the COVID-19 pandemic. The model combines clustering, ANFIS, and metaheuristics to create an easily understandable cluster.

As a result of this system, governments and health authorities have access to the information they need to assist them in planning and making decisions. As a result of these predictions, the population will be less anxious, and their mentality will be prepared to accept and handle the upcoming phases of the pandemic.

As a result of this research gap, these research questions are posed:

i. RQ1. How can ANFIS and metaheuristics be used to evaluate countries influenced by many factors which were effective factors during the COVID-19 pandemic?
ii. RQ2. How the result of K-means and metaheuristics can be used to categorize these countries according to their political characteristics?

As part of the introduction section of the research paper, a brief description of the background of the topic, gaps in the literature, research questions, and novelty of the study are described. In the second section of the paper, we discuss the literature on the use of artificial intelligence in evaluating the performance of countries under COVID-19 as part of the literature review. In the third section, we present the mathematical formulation of the proposed model based on the valuation method. The data analysis is presented in section four of the paper. A discussion is presented toward the end of the fifth section. Finally, we summarize the findings and conclusions of the study.

2. Literature Review

After the COVID-19 outbreak, the academic community, alongside other organizations, examined the effects of COVID-19 on society from various perspectives. Countries' responses to the impacts of

COVID-19 varied based on their level of development. COVID-19 has had numerous social, economic, and health impacts on societies, which have been explored in many studies:

Al-Ma'seb *et al.,* [12] used an online questionnaire to investigate the impact of the COVID-19 pandemic on social relationships. Their results highlight the importance of beliefs about COVID-19 for family well-being.

Alizadeh *et al.,[*13] examined the social impacts of the COVID-19 pandemic using inductive content analysis and thematic analysis of literature. They identified seven main areas negatively affected by the pandemic: health, social vulnerability, education, social capital, social relationships, social mobility, and social well-being.

Hosseinzadeh *et al.,[* [14] systematically reviewed the social consequences of the COVID-19 pandemic. Their findings indicate that the pandemic has exacerbated the conditions of specific vulnerable groups, necessitating targeted policies and programs to support them.

McKibbin and Fernando [15] used global data on cases, deaths, public health and economic policy responses to illustrate alternative past and potential future pandemic trajectories. Their results show significant variation in public health and economic policy responses across countries, impacting the financial outcomes of the pandemic. Various methods have been used to analyze data and predict the spread of COVID-19 in different studies:

Sharma *et al.,* [16] aimed to develop a robust and universal method for predicting COVID-19-positive cases. They recommended an Adaptive Gradient LSTM (AGLSTM) model using multivariate time-series data. Other models used in the study included RNN, LSTM, LASSO Regression, Ada-Boost, Light Gradient Boosting, and KNN. Their results showed that AGLSTM performed better with 99.81% accuracy and required only a short time for training and prediction.

Sankalpa *et al.,* [17] predicted pandemic trends with a case study on COVID-19 in the UAE. They used machine learning and deep learning models, including LASSO Regression, Exponential Smoothing, LSTM, and bidirectional LSTM-AE, with public data from the UAE government. The univariate LSTM model with a five-day input performed best, achieving an RMSE of 275.85. This method can monitor similar infectious diseases and enhance preparedness for future pandemics.

Matta and Saraf [18] explored using various machine learning classifiers to improve the accuracy of COVID-19 predictions and reduce pressure on healthcare systems. Using confirmed case, recovery, and mortality data, they found that the Gradient Boosting classifier achieved 90% accuracy for confirmed cases, 90% for recoveries, and 92% for fatalities, representing a significant improvement over the baseline.

De Souza *et al.,* [19] and de Souza Andrade *et al.,* [20] conducted a study using machine learning to predict poor prognosis in COVID-19 positive patients and possible outcomes. Their method involved analyzing data from 8,443 patients using machine learning models, achieving a prediction accuracy of AUC 0.92, sensitivity 0.88, and specificity 0.82. The study concluded that machine learning could assist in prognosis prediction and physician decision-making, reducing the burden on healthcare systems.

The publication trend of articles on "COVID-19 in the American continent" started in 2020, with the highest number of publications in 2021 (Figure 1).

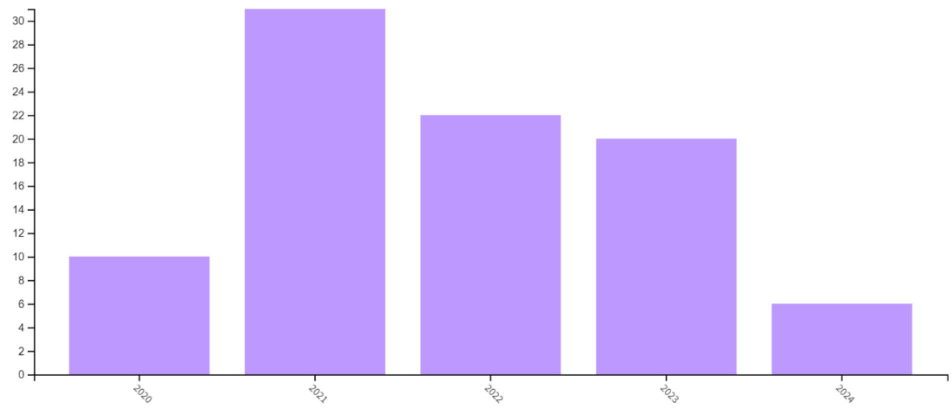

Fig. 1. The publication trend of articles on "COVID-19 in the American continent" from 2020 to 2024

Researchers from the USA, Brazil, Canada, and Spain (Figure 2) have conducted most studies on "COVID-19 in the American continent".

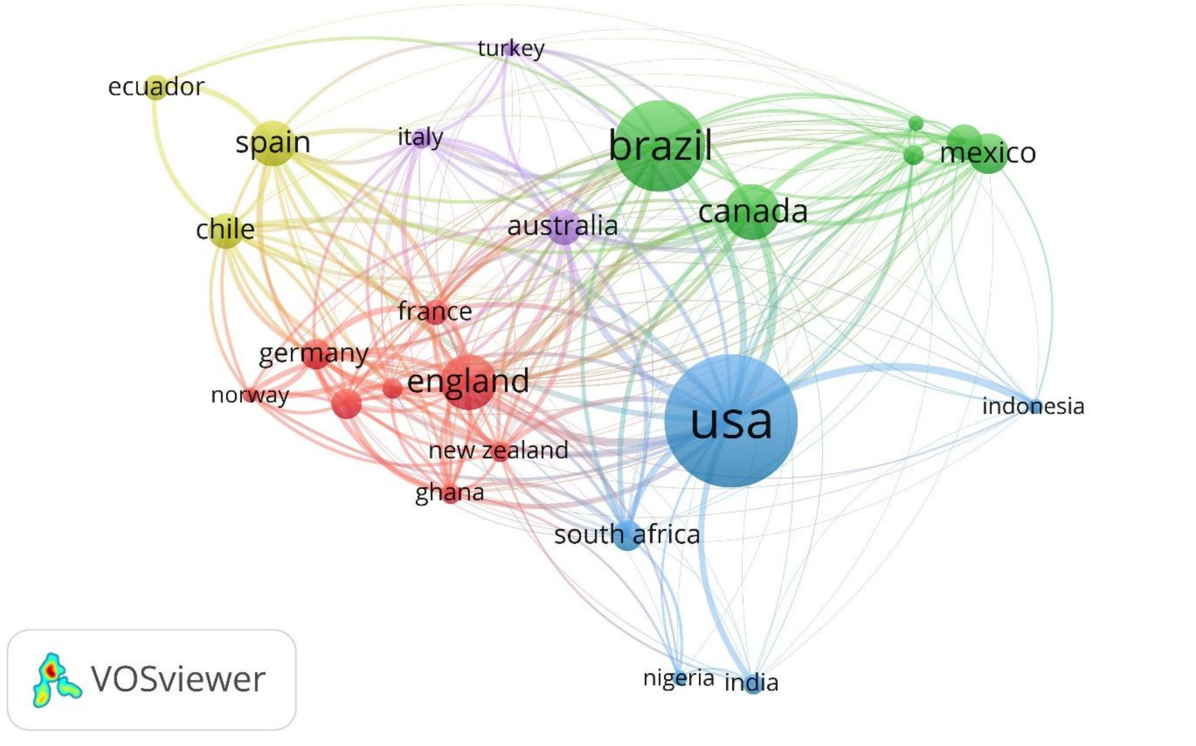

Fig. 2. Countries with the most studies on "COVID-19 on the American continent

3. Research Methodology K-means Algorithm

Clustering methods encompass various methodologies to assemble elements' groupings [21]. One aim is to guarantee that the items within the same cluster exhibit higher comparability among themselves than those positioned outside. Data mining, the practice of detecting and analyzing patterns and trends within datasets, is widely used in several disciplines, such as epidemiology, marketing, and biology [22-24]. Using these clustering methodologies, researchers may gain valuable insights into intricate data, uncover previously unnoticed patterns, and reach educated conclusions. When used in the COVID-19 pandemic, clustering methodologies can reveal transmission patterns, identify vulnerable populations, and assess treatment effectiveness. These insights inform targeted interventions in public health [25].

3.1 ANFIS-PSO

ANFIS combines the learning ability of neural networks with the reasoning method of fuzzy logic, which mimics the workings of the human mind. This strategy is versatile and valuable when modelling complicated, nonlinear systems, particularly when establishing exact mathematical models, which is as challenging as locating a needle in a haystack. ANFIS provides a resilient framework that efficiently tackles intricate, nonlinear issues in several domains, akin to a proficient tightrope walker maintaining balance on a slender wire [26,27]. It leverages the advantages of fuzzy logic and neural networks, working together seamlessly to provide a highly effective outcome. Layer 1: Adaptive nodes in the first layer are square (n.m) nodes:

$$O^1_{i,j} = \mu_{A_{i,j}}\left(X_i\right) \tag{1}$$

X_i $(0 \le i \le n-1)$ the ith input is the jth linguistic label of input of the ith which is demonstrated as $A_{i,j}$ $(0 \le j \le m-1)$ and displays the small, normal, and large numbers. Ai is the membership function of j and for the satisfaction of quantifier in specifying the degree of Ai is Xi for choosing a Generalized Bell or Gaussian membership function that shows a value of 0 and value of 1:

$$\mu_{gBell}(x) = \frac{1}{1+\left|\frac{x-c_k}{a_k}\right|^{2b_k}} \qquad \mu_{gauss}(x) = exp\left[-\left(\frac{x-c_k}{s_k}\right)^2\right] \tag{2}$$

the non-linear parameter set of the kth node is shown as $[a_k, b_k, c_k]$ $(0 \le k \le n.m-1)$ or $[s_k, c_k]$. The Ai membership function will exhibit variability depending on the values assigned to these parameters.

First, we consider that $i * m + j = k$.

Layer 2: layer contains m^n is fixed nodes. The kth is $(0 \le k \le m^n - 1)$ that perform of T-norm for incoming signals, the incoming signals of the node collect as follows:

$$O^2_k = w_k = \prod_{i=0}^{n-1} \mu_{A_{i,j}}(X_i) \tag{3}$$

The firing strength rule, denoted as wk, applies here. To calculate wk, the first layer must have a specific and well-defined number of nodes.

Layer 3: The layer of three contains m^n and fixed nodes label n for k^{th} node, and it is $(0 \le k \le m^n - 1)$

k^{th}which is the ratio of the rules firing to the sum of all rules' k^{th} is a rule's weight or normalized firing strength and it is calculated as:

$$O^3_k = \overline{w}_k = \frac{w_k}{\sum_{i=0}^{m^n-1} w_i} \tag{4}$$

Layer 4: This layer is presented with Adaptive nodes as , and the function of kth node is :

$$O^4_k = \overline{w}_k f_k = \overline{w}_k\left(\sum_{i=0}^{n-1} p^k_i x_i + r_k\right) \tag{5}$$

demonstrates sets of parameter kth node. They are linear parameters, referred to as the consequent parameters here. Figure 1 shows the ANFIS model.

Within layer 5, only a single node exists. The node's computation of the overall output involves summing up all the incoming signals, as detailed below.

$$O^5_k = output = y = \sum_{k=0}^{m^n-1} \overline{w}_k f_k = \frac{\sum_{k=0}^{m^n-1} w_k f_k}{\sum_{k=0}^{m^n-1} w_k} \tag{6}$$

Figure 3 describes the schematic of the ANFIS method.

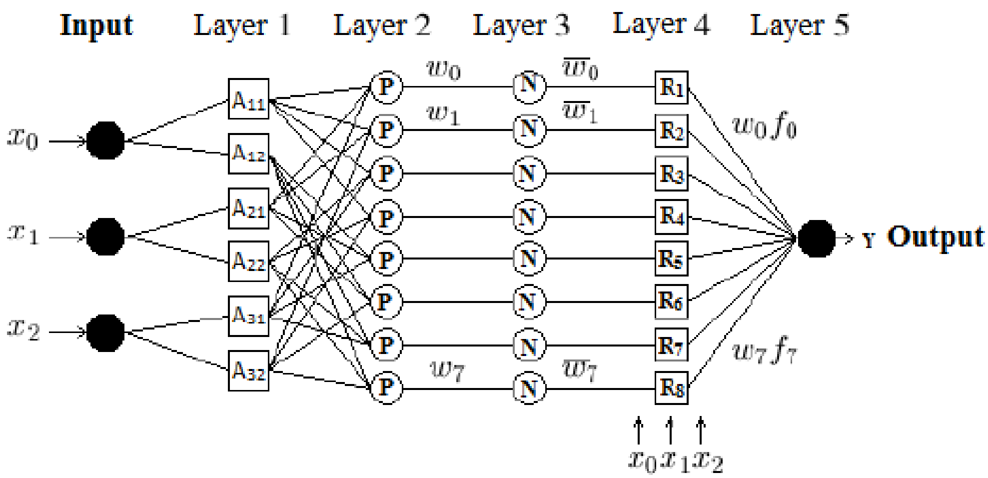

Fig. 3. Schematic of ANFIS method

3.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is like a powerful engine, revving up to optimize a wide range of functions with its computational prowess [28,29]. The algorithm falls under the genre of swarm intelligence algorithms since it swarms like a flock of birds or schools of fish. Particle Swarm Optimization (PSO) is as effective as a well-oiled machine, especially when the search space is as vast as an endless ocean, as intricate as a complex puzzle, or as mysterious as a hidden treasure. The Particle Swarm Optimization (PSO) method is like a skilled explorer, fearlessly venturing into the search space and uncovering optimum or nearly optimal solutions by harnessing the power of social interactions amongst particles. This property sets PSO apart like a shining star in the sky, making it as successful as a well-oiled machine. The PSO algorithm requires the implementation of two relations.

The velocity of particle i can be updated using the equation provided below.

$$v_{id}(t+1) = wv_{id}(t) + c_1r_1(t)(p_{id}(t) - x_{id}(t)) + c_2r_2(t)(p_{gd}(t) - x_{id}(t)) \quad (7)$$

$$v_{id} \in (-V_{\max}, +V_{\max}) \quad (8)$$

The position of particle i, xi, is represented by this equation.

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (9)$$

For each particle
Initialize position and velocity randomly
End
Do
For each particle
Calculate fitness function
If fitness value> pBest/Then
Set current fitness value as pBest
End
Update particle with best fitness value as g Best
For each particle
Calculate new velocity
Update position
End
While (t< maximum iterations)
Post-process the result

3.3 Researchers Procedure

First Step: Screening features of the evaluation. According to ANFIS-PSO, the feature of evaluating American countries is customized in this step.

Second Step: These countries are used based on the K-means and PSO algorithms for clustering.

Third Step: A scenario based on K-means clustering is depicted in this step.

Figure 4 shows the procedure.

Fig. 4. Research procedure

3.4 Data gathering

The COVID-19 database evaluation factors included Confirmed, Deaths, Recovered, Active, New cases, new deaths, newly recovered, deaths per confirmed/100 Cases, recovered per confirmed/100 Cases, Deaths/100 Recovered, Confirmed last week, one-week change, and one-week % increase.

4. Results

4.1. Data Analysis

First, ANFIS and PSO perform a preliminary evaluation of the factors to determine whether they are interconnected. A model consists of 13 factors, but only 11 need to be selected and impacted on one another for the model to work. The analysis includes various factors: Confirmed, Deaths, Recovered, Active, New cases, new deaths, new recovered, Deaths / 100 Cases, Recovered / 100 Cases, Deaths / 100 Recovered, and Confirmed last week. A list of factors that impact the outcome is shown in the figure below, along with a description of each factor. The results were obtained using the MATLAB 2022b version developed by MathWorks. The number of swarms in this model was 200, and the number of matrix iterations was 35. The analysis results show that the MSEtr is 2.6031e-04, and the MSEts is 0.2454. The following formula must be used to calculate the final default rate applied to this formula. Rate of default=$\sqrt{(2\&MSEts)}/2\times100=0.8\%$. This means that this model's error was 0.8 percent. Figure 5 shows the results of ANFIS and PSO. The time of calculation is 85.293 seconds.

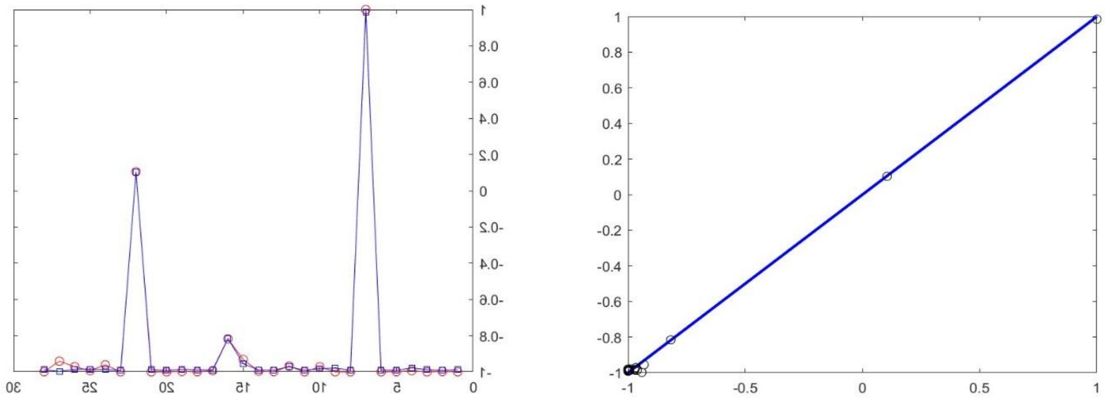

Fig. 5. results of customized feature

The model of the train is shown in Figure 4. As seen from the blue line, all the factors are close to each other; therefore, this model is best suited for training models. The performance of the test model is illustrated in Figure 4. The above figure shows that all the factors (blue and red points) are covered by each other, and this line also represents the most accurate fit of the model based on all factors. Moreover, all black points are fitted on the blue line, indicating that all the data are fitted. Thus, we can conclude that the model resulting from the exercise has a high level of reliability.
The K-means and PSO methods were combined to cluster the data. Figure 6 shows the results of the K-means and PSO methods.

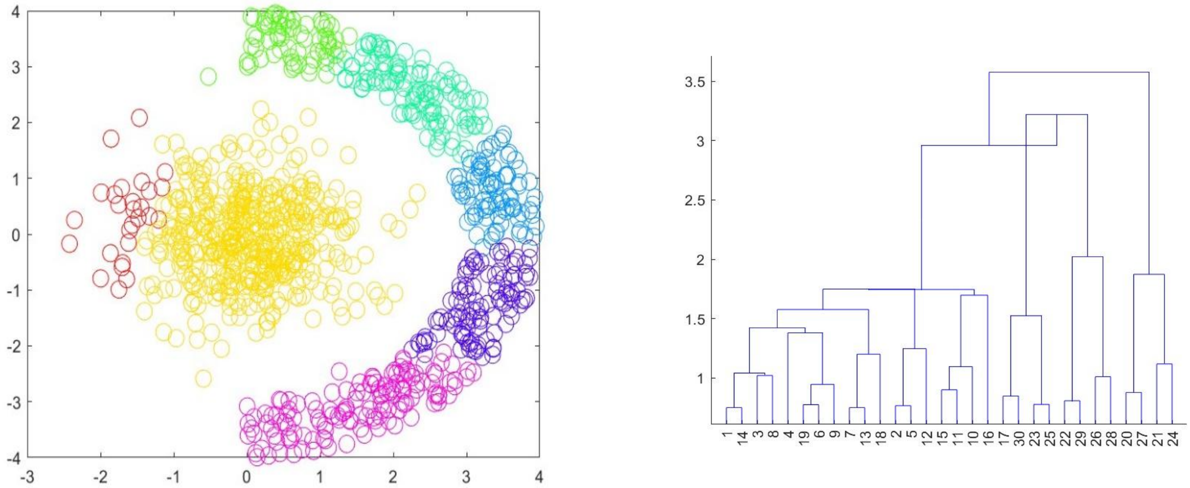

Fig. 6. Clustering and PSO

The result of K-means clustering and PSO is shown in Table 1.

Table 1
Result of clustering

Names of Countries	Cluster
Chile, Mexico, Peru	1
US	2
Colombia	3
Argentina, Barbados	4
Antigua and Barbuda, Bahamas, Barbados, Belize, Costa Rica,Cuba,Dominica, El Salvador,Grenada, Guyana,Haiti, Jamaica, Nicaragua, Paraguay, Uruguay,Venezuela, Saint Kitts and Nevis,Saint Lucia,Saint Vincent and the Grenadines,Suriname,Trinidad and Tobago	5
Bolivia, Dominican Republic,Ecuador, Guatemala, Honduras, Panama,	6
Brazil	7

Table 2 shows the number of memberships of clustering.

Table 2
Membership of clustering

Numbers of Countries	Cluster
3	1
1	2
1	3
2	4
21	5
6	6
1	7

Finally, the heat map of data is shown in Figure 7.

Fig. 7. Heat map of data

5. Discussion

The results of this research can be categorized into seven categories based on the K-means and PSO methods. Regarding category two, the US States has the poorest performance against coronaviruses. In the heat map, it can be seen that many of the features of this country are green in this regard. In Cluster 7, Brazil is a member of the following cluster. In terms of coronavirus performance, this country performed the worst after the US. Third, there is a category called Category 5. Among the high number of countries included in this category, the performance of American countries is among the worst. A fourth high-risk country is part of category three (middle category) regarding how to deal with COVID-19. The fifth category deals with the average performance of COVID-19 patients. This category is called Category Four. The sixth category is that they have accomplished a good job of solving the problems that have arisen due to the widespread use of COVID-19. As the final category, these countries have shown exemplary performance in dealing with Coronavirus compared to others.

6. Conclusion

The purpose of this study was to evaluate the performance of countries in terms of COVID-19. However, countries must know what factors affect the evaluation and what methods must be used to accomplish this job to achieve their objectives. For example, Artificial Intelligence (AI) methods can help countries understand and benchmark their performance against best practices and learn from their mistakes. Countries must overcome many obstacles when they are evaluated. In the past, it was possible to use various methods such as Gaussian, statistics, stochastics, and neural networks. Metaheuristics were employed in tandem with ANFIS and K-means, like a strong trio of superheroes, to analyze the performance of countries in the Americas in dealing with COVID-19, much as an intelligent detective uses a magnifying glass to uncover a complicated crime. The study looks forward to identifying the American countries that managed the pandemic and a well-oiled machine. Eleven out of thirteen factors were utilized to assess performance, like a hawk scanning its prey. This resulted in discovering seven distinct clusters among the thirty-five countries studied, like stars spread throughout the night sky. According to the facts, the United States handled the COVID-19 outbreak like a sinking ship on a rough sea. In contrast, three other countries' responses to the outbreak were as striking as a shooting star flashing across the night sky. The research underlines the need to recognize nations that have shined like stars in crisis management to understand and replicate their strategies, much like a talented artist recreating a masterpiece.

Using the ANFIS and PSO algorithms, 13 factors were reduced to eight factors affecting these factors for the first time. Combining the two techniques, these countries were clustered using PSO and the K-means algorithms. As a result of this study, the best-performing country was identified.

They plan to implement a better program to deal with the pandemic. A hybrid ANFIS and PSO approach was used for the first question to extract and evaluate relevant factors. Hybrid AI methods, K-means, and PSO have been applied to cluster these countries based on their performance. This study concludes with a question regarding Chile's performance among these countries. Lack of access to all relevant data is one of the most significant limitations of this study. Consequently, researchers may be able to formulate other meta-heuristics based on the findings of previous studies. Other metaheuristic methods should also be considered in future studies.

Conflict of Interest declaration
There is no conflict interest

Conflicts of Interest
The authors declare no conflicts of interest.

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