COVID-19 Crisis Management: Global Appraisal using Two-Stage DEA and Ensemble Learning Algorithms

Ali Taherinezhad, Alireza Alinezhad*

Faculty of Industrial and Mechanical Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran.

Abstract: Today, coronavirus disease 2019 (COVID-19) is a big crisis for the world. The infected countries are attempting to manage this crisis with various strategies and maximum medical capacity, but they have not been much successful. Due to the rapid growth of COVID-19 data, this paper investigated an integrated approach for performance evaluation of countries at any time of the COVID-19 pandemic. The strategies implemented in countries were summarized in three systems: prevention, infection detection, and medical. In Phase 1, after variable selection, data were collected for 100 countries with the highest infected cases by June 21, 2021. Then, mathematical modeling of two-stage data envelopment analysis with desirable-undesirable variables was performed using three basic ideas: independent, connected, and relational. By solving the relational model, the efficiency scores of the countries were obtained, and they were categorized into four classes based on these results. In Phase 2, 80% of the data were considered as training samples to generate a machine learning model via ensemble methods. In Phase 3, the class of test samples was predicted using the optimal ensemble model. The results showed that in a small dataset, the Bag algorithm had 95% accuracy in predicting the class of test samples.

Keywords: Coronavirus pandemic, Desirable-undesirable variables, Relational DEA model, Ensemble learning, Small-scale datasets classification.

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1. Background

As of December 31, 2019, a highly contagious disease caused by a novel coronavirus (SARS-CoV-2 short for Severe Acute Respiratory Syndrome Coronavirus-2) originated in Wuhan, Hubei Province of China [1, 2]. As of February 11, 2020, the World Health Organization (WHO) named the disease COVID-19, short for "coronavirus disease 2019" [3]. By June 21, 2021, the disease had spread to more than 190 countries worldwide [4, 5]. Globally, until this date, there were 179,393,155 confirmed cases of COVID-19, including 3,884,890 deaths and 163,989,148 recovered cases [6]. Since its initial identification, despite many efforts to manage the COVID-19 pandemic, the virus is now the biggest threat to world health and the economy [7]. In each country, the virus infection rate varies according to national and geographical conditions [8]. Therefore, policymakers, scientists, and researchers clearly adopt and implement different control strategies for the disease [9, 10]. Now one main question arises: to what extent have countries been successful in managing the coronavirus crisis so far?

Data envelopment analysis (DEA) is a powerful mathematical tool that can answer this question. The first DEA model was proposed by Charanes et al. [11]. Many kinds of research that evaluate decision-making units (DMUs) in an extensive range of contexts have been proposed in recent years [12-20]. See Emrouznejad and Yang [21] for a literature review of DEA.

In the DEA approach, each unit receiving several inputs and producing several outputs is known as a DMU [22]. Accordingly, this paper investigated each country as a DMU. The correct selection of variables reflecting countries' efficiency is of particular importance. To this end, we must know that all coronavirus control strategies are implemented in three systems: prevention, infection detection, and medical. Next, with correct knowledge of the inputs and outputs of these three systems, we selected variables to form a DEA model. The problem now is that the DEA model measures countries' efficiency only at a given time of the pandemic, and due to the rapid growth of COVID-19 data, measuring performance at any given time of the

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* *Correspondence (Mobile: +98 9123342560).*
E-mail: atqiau@gmail.com (Ali Taherinezhad), alalinezhad@gmail.com (Alireza Alinezhad).

pandemic requires the re-implementation of DEA models, which is very time-consuming and requires computer resources. Machine learning (ML) techniques can resolve this issue by predicting DMUs' efficiency [23]. In ML, supervised algorithms predict the target (classification or regression) of test samples by generating a model from training samples [24]. In large datasets, the model can have lower prediction error with more training samples. However, the main challenge is small datasets whose data is growing and changing rapidly.

Based on the mentioned points, the research objectives are as follows:

- The first goal is to present a model of DEA to measure the countries' efficiency in COVID-19 crisis management. In this study, the effectiveness of 100 countries was measured from the beginning of the pandemic to June 21 of 2021, using a two-stage DEA modeling. It is noteworthy that the measured performance scores only relate to this period.
- The second goal is to predict the countries' efficiency at any given time from the beginning of the COVID-19 pandemic based on the results of the DEA model. Accordingly, this study classifies the efficiency values of countries into 4 classes. In this way and using classification algorithms, each country's range of efficiency scores can be predicted with high accuracy.

After clarifying research objectives, some questions arise, answering which may clarify the necessity of this research. Questions such as:

- What is the main purpose of classifying the countries?
- What are the main outcomes of predicting countries' efficiency?
- Why do we need to predict it?
- In what areas the results of this research can be used?

According to the small dataset under study, the main purpose of classifying countries is to use the classification algorithms and have high accuracy in predicting the range of efficiency scores. This classification is done because classification algorithms perform much better than regression algorithms in small datasets. The main outcomes of predicting countries' efficiency are the conservation of computer resources and saving time for measuring efficiency. As mentioned earlier, given the rapid growth of COVID-19 data, DEA calculations will require vast computer resources and time. During the COVID-19 pandemic, countries' statistics and data are growing rapidly. Making management decisions and policies to control the pandemic requires knowing what level of performance each country has at a given pandemic time and how efficient it has been. Thus, predicting the efficiency of countries can provide the governments, policymakers, and healthcare systems with deep insight to make the right decisions for crisis management in the future. This research can be used in social and medical areas and at the macro level for health policymakers in governments.

The paper was organized as follows: Section 2 reviewed related studies. Section 3 explained the integrated method of DEA and ML. Results and discussion were presented in Section 4. Finally, Section 5 provided the summary and conclusion.

2. Related Studies

2.1. Data Envelopment Analysis & Machine Learning (DEAML)

In recent years, various studies have focused on DEA and ML (DEAML). In most of these studies, the DEAML approach has been used to examine variables with the most significant impact on DMUs' efficiency [25-30]. Other research has studied DMUs' efficiency prediction [31, 32]. Gupta et al. [31] used DEA to evaluate the relative energy performance of residential buildings. Focusing on the problem of effective preprocessing of a dataset for artificial neural network (ANN) training, Misiunas et al. [25] implemented the DEANN method to predict the functional status of patients in organ transplant operations. De Clercq et al. [26] used a combination of DEA and stochastic gradient boosted model to classify and isolate efficiency determinants of projects in Germany and the United States (industrial-scale biogas facilities). Liu and Zhan [27] evaluated the financing efficiency of the 39 listed agricultural companies in China from 2013 to 2017 based on the DEA method. Mirmozaffari et al. [28] used ML clustering algorithms and DEA to evaluate the performance of 30 banks from eight developing countries. Nandy and Singh [32] provided the DEA combined approach and the random forest (RF) algorithm to evaluate and predict environmental variables of 450 paddy producers in East Indian villages. Rebai et al. [29] conducted a study using regression trees and random forests to identify main factors affecting the academic performance of Tunisian secondary schools. Salehi et al. [30] carried out the first study with an integrated DEA and multi-layer perceptron approach. The two studies underlying this paper are now reviewed.

Emrouznejad and Shale [33] proposed a neural network back-propagation DEA (NNDEA) algorithm to solve the problem of measuring efficiency in large-scale datasets. One reason for choosing this approach was the compatibility of DEA and neural network back-propagation algorithm. Following previous research, Zhu et al. [23] measured the efficiency of Chinese listed companies in 2016 with a large dataset using the DEA-CCR (Charnes-Cooper-Rhodes) model. In this study [23], likewise the study by Emrouznejad and Shale [33], the reason for choosing the combined approach of DEA and ML algorithms is the rapid growth of DMUs data in large datasets. This paper continues the approach in these two studies, with the difference that the present study focused on small data. In the two previous studies, DEA results were considered as a regression target. The large dataset they examined made it possible to predict efficiency scores accurately. This is difficult in a small dataset because there are limited training samples for model generation [34]. This paper investigated a different approach to small data management.

2.2. DEAML & COVID-19

Now, the research background was reviewed from another aspect. The purpose was to review articles using DEA or ML or a combination of them (DEAML) in COVID-19 studies. To prevent coronavirus transmission, especially COVID-19, Loey et al. [35] proposed a hybrid deep and machine learning model for face mask recognition. Ordu et al. [36] evaluated the performance of the healthcare systems of 16 countries in preventing the COVID-19 pandemic. Their objective was to enable health policymakers to better manage the fight against the disease outbreak and implement emergency action plans immediately. In another study, Mariano et al. [37] comparatively assessed the Brazilian states in COVID-19 management using the DEA Network. Their purpose was to assist health policymakers and decision-makers in the Brazilian states to implement disease prevention measures. Nepomuceno et al. [38] conducted a study using a two-stage DEA model to find empty hospital beds and reallocate them to the patients during the COVID-19 pandemic.

There have been studies that examined the effects of COVID-19 from a psychological perspective. For example, Yeasmin et al. [39] examined the effects of COVID-19 on the mental health of Bangladeshi children. Overall, this study showed that children suffered from depression, anxiety, and sleep disorders.

Other extensive studies in COVID-19 have been performed using ML algorithms, some of which are reviewed here. For instance, Ahamad et al. [40] used ML models to predict COVID-19 positive patients. They aimed to identify significant symptoms of COVID-19 patients using ML models. Malki et al. [41] investigated the relationship between climate data and COVID-19 mortality rates. Despite extensive research papers on COVID-19 case studies, identifying applied papers is time-consuming and impractical. For this reason, Sonbhadra et al. [42] proposed a method aimed at extracting the COVID-19-related research process using ML approaches. Mahmoudi et al. [43] used the fuzzy clustering approach and compared the distributions of COVID-19 outbreaks in the United States, Spain, Italy, Germany, the United Kingdom, France, and Iran. This study aimed to investigate the relationships between coronavirus outbreak distributions to determine medical policies. In another study, Imtyaz et al. [44] sought to achieve the best response to COVID-19 by analyzing the reactions of different states in the disease pandemic. Guerrero et al. [45] used the ML, and specifically the decision tree method. These authors sought to create profiles of children and adolescents in Canada who followed more str5ictly or less strictly the 24-hour health guidelines during the outbreak of COVID-19. Mei et al. [46] compared and classified the risk of infection by COVID-19 and influenza using hierarchical methods. In another study, using a new three-stage approach based on the DEA and ML, Aydin and Yurdakul [47] examined the performance of 142 countries in controlling the prevalence of COVID-19. In addition, they investigated the effect of the factors of the number of patients, recovered cases, and deaths. For a quick review, the searched articles are listed in Table 1.

As shown in Table 1, only the last study used the DEAML approach in the COVID-19 scope, DEA and ML were used alone in the rest of the studies. ML methods in these studies were limited to five methods, including K-means [39, 42, 43, 44, 47], hierarchical [42, 46, 47], decision tree [40, 41, 45, 47], random forest [40, 41, 47], and support vector machines [35, 40, 41, 42]. Now that the aims of these articles were clearly stated, we compare the mentioned articles with the present research from the perspective of case study and methodology. Among the mentioned researches, only three studies have measured the efficiency of nations or states in COVID-19 crisis management [36, 37, 47]. However, none of the previous research has addressed the rapid growth of COVID-19 data and its effect on efficiency measurement through DEA. This critical issue in this regard is the gap of previous studies examined in this research. Focusing on the problem of the rapid growth of COVID-19 data and finding an answer for it has made the methodology of this article different from previous articles. Based on what was stated in Section 2.1 and Section 2.2, the novelties and key contributions of the research are as follows:

- Focusing on measuring the efficiency of DMUs in small datasets when data is growing rapidly (COVID-19 case study).
- Measuring the efficiency of 100 countries in COVID-19 crisis management until June 21 of 2021 through relational two-stage DEA modeling and the use of desirable and undesirable variables.
- Using ensemble algorithms to predict efficiency and classify countries with high accuracy.

3. Material and Methods

3.1. Structure of research methodology

The structure of research methodology was summarized in the following 3 phases:

- ❖ **Phase 1:** In this phase, after selecting DEA variables, their data was collected. For variables to have the same effect on efficiency scores, the data were normalized. Then, mathematical modeling was performed. By solving the model, the countries' efficiency scores were obtained. Finally, based on the DEA results, the countries were classified into four classes: A, B, C, and D. The second phase of the research methodology (i.e., usage of machine learning techniques) to predict the efficiency class of countries in managing the COVID-19 pandemic (i.e., A, B, C, and D) is based on results generated by the two-stage DEA method.

- ❖ **Phase 2:** In this phase, the purpose was to generate an ML model to predict the class of countries. First, outlier data that could have a significant impact on model generation was detected and removed. Then, the data were normalized. After normalization, 80% of the data were considered as training samples. The model was trained using ensemble methods. Finally, by optimizing the parameters, an optimal model was generated. In this phase, the model accuracy in predicting the class of training samples was evaluated.

- ❖ **Phase 3:** In this phase, 20% of the data were used as test samples to assess the model's actual accuracy. The test samples were entered into the generated model to predict a new class. By comparing the new and actual classes of each sample, the model's actual accuracy was evaluated.

For a better knowledge of research methodology, see Figure 1.

3.2. COVID-19 crisis management systems

As mentioned in Section 1, correctly comparing the countries and measuring their efficiency require the correct selection of variables. A prerequisite for this is to know what actions countries have taken to manage the coronavirus crisis, in what systems these actions have been taken, and what the results have been. Therefore, crisis management systems were examined first.

In this paper, coronavirus crisis management strategies were summarized in three systems. The first system is a prevention system in which strategies include vaccination, quarantine, school and university closures, restrictions on business, and adherence to health protocols, such as use of masks and social distance. These strategies affect the total infected cases. The second system is the infection detection system. In this system, strategies focus on COVID-19 disease diagnosis. Infection detection is performed using COVID-19 test kits, such as the polymerase chain reaction test. In addition, due to the significant negative results of diagnostic kits, doctors and specialists use lung CT scans as a tool for infection detection. This system's actions also affect the number of infected cases because the output of each test determines whether a person is infected with the coronavirus. The third system is the medical system in which sick people are treated. System resources include hospital beds, intensive care unit (ICU) beds, and ventilators. Obviously, the medical system's actions also affect the number of patients improved and the mortality rate. Figure 2 shows the systems and their inputs and outputs [6, 48]. The inputs and outputs were numerical, and qualitative variables were not considered.

3.3. Decision variables and parameters

Now, the purpose was to select DEA variables from the numeric inputs and outputs (Figure 2). Based on this study's approach, the course of infection detection was evaluated until complete recovery. Variables selected to form the two-stage DEA model (Figure 3) were as follows:

- **Tests:** The total number of COVID-19 tests (Tes).
- **Total cases:** The total number of patients infected with coronavirus ($TCas$).
- **Active cases:** The total number of patients not recovered whose disease was active ($ACas$).
- **Recovered cases:** The total number of patients recovered (Rec).
- **Deaths:** The total number of patients not recovered whose disease resulted in death (Dea).

3.4. Mathematical modeling

3.4.1. Management of desirable-undesirable variables

The general DEA approach reduces input (resources) and increases output. Inputs and outputs evaluated in this way are known as desirable variables [49, 17]. However, in the real world, sometimes evaluating decision-making units may require undesirable variables. The case study presented in this paper was one of these examples. According to Figure 3, as the tests increased and total and cases remained constant, the countries' efficiency increased, meaning that fewer people were infected with the coronavirus. In fact, in Stage 1, we aimed to increase the tests but decrease total and active cases. This is exactly the opposite of the basic DEA approach; thus, the tests, total cases, and active cases variables were undesirable. In Stage 2, more infected cases must be selected for further recovery, similar to water treatment, where more contaminated water must be processed for further treatment. As a result, a country with more recovered cases and fewer deaths will be more efficient. Therefore, the recovered cases and deaths variables were desirable and undesirable, respectively.

Several methods have been proposed for managing undesirable variables. See Liu et al. [49] for a summary review of methods. The method used in the present paper considered undesirable inputs (undesirable outputs) as desirable outputs (desirable inputs). This method was first proposed by Färe and Grosskopf [50]. To better understand how this method works, first consider Model 1, known as the envelopment form of the BCC (Banker-Charnes-Cooper) model (output oriented) [51]:

$$
\begin{aligned}
&Maximize\ \ \phi_k\\
&Subject\ to\begin{cases}\sum_{j=1}^{n}\lambda_j.x_{ij}\le x_{ik} & ,\ i=1,2,\ldots,m\\ \sum_{j=1}^{n}\lambda_j.y_{rj}\ge \phi_k.y_{rk} & ,\ r=1,2,\ldots,s\\ \sum_{j=1}^{n}\lambda_j=1\ ,\ \lambda_j\ge 0\ ,\ \phi_k\ free;\ j=1,2,\ldots,k,\ldots,n & \end{cases}
\end{aligned}
\qquad (1)
$$

where m is the number of inputs and s is the number of outputs; Here, x_i represents the input i and y_r represents the output r for the kth DMU. Now suppose x_{ik}^{DI} represents desirable inputs and $x_{i'k}^{UI}$ represents undesirable inputs. Also, y_{rk}^{DO} shows desirable outputs and $y_{r'k}^{UO}$ indicates undesirable outputs for the kth DMU in this single-stage model. Based on Färe and Grosskopf's method [50], Model 2 for managing undesirable variables was written as follows:

$$
\begin{aligned}
&\text{Maximize } \ \phi_k \\
&\text{Subject to}\begin{cases}
\sum_{j=1}^{n}\lambda_j.x_{ij}^{DI} \le x_{ik}^{DI} & , \ i=1,2,\ldots,m \\
\sum_{j=1}^{n}\lambda_j.y_{r'j}^{UO} \le y_{r'k}^{UO} & , \ r'=1,2,\ldots,s' \\
\sum_{j=1}^{n}\lambda_j.x_{i'j}^{UI} \ge \phi_k.x_{i'k}^{UI} & , \ i'=1,2,\ldots,m' \\
\sum_{j=1}^{n}\lambda_j.y_{rj}^{DO} \ge \phi_k.y_{rk}^{DO} & , \ r=1,2,\ldots,s \\
\sum_{j=1}^{n}\lambda_j = 1 \ , \ \lambda_j \ge 0 \ , \ \phi_k \ free; \ j=1,2,\ldots,k,\ldots,n
\end{cases} \qquad (2)
\end{aligned}
$$

3.4.2. The basic ideas in efficiency measurement for DEA network systems

In this part, for mathematical modeling of two-stage DEA (Figure 3), three basic ideas in modeling network systems were described [22]:

- ❖ **Independent model:** The most straightforward way to investigate a network system's performance is to measure the efficiency of each of its divisions by treating them as independent DMUs. Based on this idea and using the mentioned approach to manage undesirable variables (Model 2), Model 3 was written as follows:

$$
\begin{aligned}
&\text{Maximize } \ \phi_k^{(1)} + \phi_k^{(2)} \\
&\text{Subject to}\begin{cases}
\sum_{j=1}^{n}\lambda_j^{(1)}.Tes_j^{UI} \ge \phi_k^{(1)}.Tes_k^{UI} \\
\sum_{j=1}^{n}\lambda_j^{(1)}\left(TCas_j^{UO} + ACas_j^{UO}\right) \le \left(TCas_k^{UO} + ACas_k^{UO}\right) \\
\sum_{j=1}^{n}\lambda_j^{(2)}\left(TCas_j^{UI} + ACas_j^{UI} + Rec_j^{DO}\right) \ge \phi_k^{(2)}\left(TCas_k^{UI} + ACas_k^{UI} + Rec_k^{DO}\right) \\
\sum_{j=1}^{n}\lambda_j^{(2)}.Dea_j^{UO} \le Dea_k^{UO} \\
\sum_{j=1}^{n}\lambda_j^{(1)} = 1 \ , \ \sum_{j=1}^{n}\lambda_j^{(2)} = 1 \\
\lambda_j^{(1)}, \lambda_j^{(2)} \ge 0 \ ; \ \phi_k^{(1)}, \phi_k^{(2)} \ free \ ; \ j=1,2,\ldots,k,\ldots,n
\end{cases} \qquad (3)
\end{aligned}
$$

By solving the model, the values $\phi^{(1)*}$ and $\phi^{(2)*}$ were obtained in the range $[1,+\infty)$. The obtained values must be reversed to determine each stage's efficiency. This model cannot measure the entire network's efficiency.

- ❖ **Connected model:** Färe and Grosskopf [52] formulated a production possibility set for a network system. They used distance functions defined on the production possibility set as the system's efficiency. Kao [53] named this model the connected model. Based on this idea, Model 4 was written as follows:

$$
\text{Maximize } \phi_k^{Connected}
$$

$$
\text{Subject to}\begin{cases}
\sum_{j=1}^{n} \lambda_j^{(1)}.Tes_j^{UI} \geq \phi_k^{Connected}.Tes_k^{UI} \\
\sum_{j=1}^{n} \lambda_j^{(1)}\left(TCas_j^{UO} + ACas_j^{UO}\right) \leq \left(TCas_k^{UO} + ACas_k^{UO}\right) \\
\sum_{j=1}^{n} \lambda_j^{(2)}\left(TCas_j^{UI} + ACas_j^{UI}\right) \geq \left(TCas_k^{UI} + ACas_k^{UI}\right) \\
\sum_{j=1}^{n} \lambda_j^{(2)}.Rec_j^{DO} \geq \phi_k^{Connected}.Rec_k^{DO} \\
\sum_{j=1}^{n} \lambda_j^{(2)}.Dea_j^{UO} \leq Dea_k^{UO} \\
\sum_{j=1}^{n} \lambda_j^{(1)} = 1 \;,\; \sum_{j=1}^{n} \lambda_j^{(2)} = 1 \;,\; \lambda_j^{(1)}, \lambda_j^{(2)} \geq 0 \;;\; \phi_k^{Connected} \; free \;;\; j = 1,2,\ldots,k,\ldots,n
\end{cases} \qquad (4)
$$

In this model, only network efficiency was obtained, and an independent model must be defined to measure each stage's efficiency.

❖ **Relational model:** Combining the concepts of Independent and Connected Models, Kao [53] proposed a relational model that could measure the efficiency of the system and its divisions. Based on this idea, Model 5 was written as follows:

$$
\text{Maximize } \phi_k^{Relational}
$$

$$
\text{Subject to}\begin{cases}
\sum_{j=1}^{n} \lambda_j^{(1)}.Tes_j^{UI} \geq \phi_k^{Relational}.Tes_k^{UI} \\
\sum_{j=1}^{n} \lambda_j^{(1)}\left(TCas_j^{UO} + ACas_j^{UO}\right) \leq \sum_{j=1}^{n} \lambda_j^{(2)}\left(TCas_j^{UI} + ACas_j^{UI}\right) \\
\sum_{j=1}^{n} \lambda_j^{(2)}.Rec_j^{DO} \geq \phi_k^{Relational}.Rec_k^{DO} \\
\sum_{j=1}^{n} \lambda_j^{(2)}.Dea_j^{UO} \leq Dea_k^{UO} \\
\sum_{j=1}^{n} \lambda_j^{(1)} = 1 \;,\; \sum_{j=1}^{n} \lambda_j^{(2)} = 1 \\
\lambda_j^{(1)}, \lambda_j^{(2)} \geq 0 \;;\; \phi_k^{Relational} \; free \;;\; j = 1,2,\ldots,k,\ldots,n
\end{cases} \qquad (5)
$$

The independent model measures only the efficiency of the stages or divisions (See Model 3). In this model, it is not feasible to directly measure the whole network's efficiency. On the other hand, the connected model can only measure the efficiency of the whole network, but not the efficiency of the stages or divisions (Model 4). The relational model is a comprehensive model that covers the weaknesses of the previous two models. In this study, the relational model was used to measure efficiency (Model 5). Using a relational model allows measuring the efficiency of the whole network and stages. Although this study only considers the efficiency of the whole network and does not examine the efficiency of each stage separately, using a relational model can facilitate the task for other researchers to examine the efficiency of stages in this study more accurately. After solving the model, the values $(\phi_j^{Relational^*})^{-1}$ showed the countries' efficiency scores.

3.5. Ensemble learning

As shown in Figure 1, Phases 2 and 3 were related to ML techniques in which ensemble methods were used. Ensemble learning is a general approach to machine learning that seeks better predictive performance by combining predictions of several models [54]. The goal of ensemble methods is to construct a set of learners and combine them, while ordinary learning approaches try to construct one learner from training data [55]. Figure 4 shows a common architecture of ensemble methods. The three main classes of ensemble learning methods are bagging, stacking, and boosting [56]. This paper used three algorithms, including Bag, Adaptive Boost, and Random Under-Sampling Boost, to generate an optimal model.

Bagging. One of the problems for classifying datasets is the limited size of the training set. One of the best solutions for problems with small training datasets is to use the bagging algorithm [56, 57]. The bagging (short for bootstrap aggregation) algorithm was presented by Breiman [58] based on bootstrapping and aggregation methods. Figure 5 reflects a summary of the bagging algorithm schematically.

Adaptive boosting (AdaBoost). Another category of ensemble learning methods is boosting. Boosting algorithms can convert weak learners to strong learners [55]. One of the influential boosting algorithms is the AdaBoost (short for adaptive boosting) algorithm proposed by Freund and Schapire [59]. This is an algorithm for binary classification problems. However, in this study, we needed another version of AdaBoost known as the AdaBoost.M1 algorithm. Adaboost.M1 expands binary classification to multi-classification problems. Figure 6 presents a summary of the AdaBoost.M1 algorithm. See Alfaro et al. [56] for more details on the algorithm.

Random under-sampling boosting (RUSBoost). The RUSBoost (short for random under-sampling boosting) algorithm is one of boosting methods proposed by Seiffert et al. [60]. This algorithm is designed to improve the performance of models trained on skewed data. Figure 7 presents the RUSBoost algorithm.

3.6. Data collection

To illustrate the study's method, data were collected from the Worldometers [6] website for 100 countries with the most infected cases by 16:17 GMT (Greenwich Mean Time), June 21, 2021. For a correct comparison of the countries, the variables were per million population (per 1M pop). Statistical parameters for this dataset are presented in Table 2. In this research, we considered the countries with the highest infections for which all their variables' data were available. If variables' data were available for all countries involved with the disease, all countries would be examined in this study. Therefore, lack of access to data was one of the research limitations. Finally, we just studied countries for which there was valid data. The results and conclusions of this study are not limited to these countries and can be used and developed for other countries.

4. Results and Discussion

4.1. Data normalization and solving DEA model

According to Table 2, different ranges of variables can have an imbalanced effect on efficiency scores. One of the best ways to deal with this problem is to normalize data [61]. Here, the Manhattan Normalization (MN) method, known as L1-Norm, was used. Before explaining the L1-Norm method, first, consider the matrix $\mathbf{A}_{m\times n}$, where m represents the number of rows and n is the number of matrix columns (Eq. 6). If matrix A is considered the dataset of this study, m denotes the number of countries and n shows the number of variables in the DEA or features in the ML. If x_{ij} is an entry in row i and column j of matrix A, the L1-Norm method will be expressed by Eq. 7:

$$\mathbf{A}_{m\times n}=\begin{pmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2n} \\ x_{31} & x_{32} & x_{33} & \cdots & x_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & x_{m3} & \cdots & x_{mn} \end{pmatrix} \quad ;\, i=1,\ldots,m \quad , \quad j=1,\ldots,n \qquad (6)$$

$$x_{i,j}^{N}=\frac{x_{i,j}}{\sum_{j=1}^{n}\left|x_{i,j}\right|}=\frac{x_{i,j}}{\left\|\mathbf{x}\right\|_{1}}\ ,\ i=1,2,\ldots,m \qquad (7)$$

Where $x_{i,j}^{N}$ is the normalized value for $x_{i,j}$ in the row i and the column$j$. In this case, after normalizing the data, the sum of each column (variables) is equal to1. In this way, variables have a balanced effect on efficiency scores, meaning that they will have an equal share of efficiency.

Model 5 was implemented using normalized data in MATLAB [62] software. The results are collected in Table 3. The efficiency scores obtained (Table 3) showed the countries' performance by June 21, 2021. The problem now is that COVID-19 data is growing moment by moment. Figure 8 shows the growth rate of total cases and active cases (currently infected), globally [6]. Now, ML techniques are used to solve the problem of evaluating countries' performance at any given time in the COVID-19 pandemic. This study proposed an approach to use classification models. Accordingly, first, the countries were classified into four classes of A, B, C, and D based on efficiency scores (Figure 9) Then, the class of countries was considered as the target of classification models. The class of countries based on the DEA results is given in Table 3.

4.2. Preprocessing data for training ML model

In small datasets, outlier values can have a significant impact on predictive performance and should be excluded from statistical calculations. The best approach to deal with this problem is to replace the outlier values with the mean values called Mean Substitution (MS) [63-65]. In this step, first, outlier values in each feature (DEA variables) were detected. Finally, the calculated average replaced the outlier values. Figure 10 shows the box plot of features in this step. Descriptive statistics of the dataset after removing the outlier values are presented in Table 4.

4.3. Training via ensemble methods

In this phase, first, 20 training samples from each class were entered into the model, as shown in Figure 9. Then, three algorithms, including Bag, AdaBoost, and RUSBoost, were implemented using MATLAB [62] software to generate an optimal ensemble model. Figure 11 shows the minimum classification error plot in 30 iterations. The results showed that the Bag algorithm was the optimal algorithm for data class prediction. As shown in Figure 12, the class of all training samples was correctly predicted, and the model had 100% accuracy.

4.4. Predicting class of testing samples

In this phase, the testing data was entered into the model, and the model's real accuracy was determined. First, the generated model was fitted to the new data, and then the class of new data (test samples) was predicted. Finally, the actual and predicted classes of each sample were compared. The prediction results (Table 5) showed that the generated model had 95% accuracy in predicting the class of testing samples. Based on the observations, it can be concluded that the Bag algorithm has an excellent performance in classifying small datasets. Now, by using the generated model, it is possible to evaluate countries' performance at any time of the COVID-19 pandemic. The disadvantage of this approach is that it does not measure the efficiency score. However, the efficiency class of a country can reflect the results of strategies implemented in each country.

5. Summary and Conclusion

Generally, it is difficult to evaluate a set of decision-making units whose data is growing rapidly, because the evaluation with new data requires the re-implementation of DEA models. By considering each country as a decision-making unit, COVID-19 is a good case study on reflecting this problem. If the dataset of decision-making units is large, machine learning regression models can be a good solution for predicting efficiency scores. However, the challenge is when there are few training samples of decision-making units. In a small dataset, it is difficult to predict efficiency scores using regression models. This study observed that by classifying efficiency scores into four classes and using classification models, it was possible to evaluate countries despite the rapid growth of COVID-19 data. The results showed that the Bag algorithm had an acceptable performance in predicting small data classes. The disadvantage of the proposed approach is that it does not measure efficiency scores accurately. However, the efficiency class of decision-making units can also show an overview of their performance. The approach presented in this research can be used in a wide range of sciences to evaluate decision-making units with small scales whose data are growing rapidly.

Evaluating the performance of countries in the management of COVID-19 in an uncertain condition is one of the research areas, wherein just few studies have been conducted. Researchers are recommended to develop DEA models in uncertain conditions (e.g., Fuzzy, Gray, Neutrosophic) to evaluate countries' performance in future research. In addition, due to the global vaccination in many countries and its direct impact on the management of COVID-19, paying attention to this variable and using it in DEA models are strongly recommended. Researchers can also use DEA tools to evaluate the effectiveness of WHO-approved vaccines or evaluate the impact of each of them in different countries.

References

1. World Health Organization, Novel Coronavirus (2019-nCoV) (SITUATION REPORT-1), Reported January 20, 2020, URL https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200121-sitrep-1-2019-ncov.pdf
2. Coronaviridae Study Group. "The species Severe acute respiratory syndrome-related coronavirus: classifying 2019-nCoV and naming it SARS-CoV-2", *Nature microbiology*, **5**(4), p.536 (2020).
3. World Health Organization, Novel Coronavirus (2019-nCoV) (Situation Report –22), Reported February 11, 2020, URL https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200211-sitrep-22-ncov.pdf
4. World Health Organization, WHO Coronavirus (COVID-19) Dashboard, Updated June 21, 2021, URL https://covid19.who.int/
5. Johns Hopkins University, COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU), Updated June 21, 2021, URL https://coronavirus.jhu.edu/map.html/
6. Worldometers, Reported Cases and Deaths by Country or Territory. Updated 16:17 GMT June 21, 2021, Accessed June 21, 2021, https://www.worldometers.info/coronavirus/
7. Jacobsen, K.H. "Will COVID-19 generate global preparedness?", *Lancet (London, England)*, **395**(10229), p.1013 (2020).
8. Wang, P., Zheng, X., Li, J., et al. "Prediction of epidemic trends in COVID-19 with logistic model and machine learning technics", *Chaos, Solitons & Fractals*, **139**, p.110058 (2020).
9. Farooq, J. and Bazaz, M.A. "A novel adaptive deep learning model of Covid-19 with focus on mortality reduction strategies", *Chaos, Solitons & Fractals*, **138**, p.110148 (2020).
10. Rafiq, D., Batool, A. and Bazaz, M.A. "Three months of COVID‐ 19: A systematic review and meta‐ analysis", *Reviews in medical virology*, **30**(4), p.e2113 (2020).
11. Charnes, A., Cooper, W.W. and Rhodes, E. "Measuring the efficiency of decision making units", *European journal of operational research*, **2**(6), pp.429-444 (1978).
12. Alinezhad, A., Makui, A. and Mavi, R.K. "An inverse DEA model for inputs/outputs estimation with respect to decision maker's preferences: The case of Refah bank of IRAN", *Mathematical Sciences*, **1**(1-2), pp.61-70 (2007).
13. Alinezhad, A., Sarrafha, K. and Amini, A. "Sensitivity analysis of SAW technique: The impact of changing the decision making matrix elements on the final ranking of alternatives", *Iranian Journal of Operations Research*, **5**(1), pp.82-94 (2014).
14. Sarrafha, K., Kazemi, A. and Alinezhad, A. "A multi-objective evolutionary approach for integrated production-distribution planning problem in a supply chain network", *Journal of Optimization in Industrial Engineering*, **7**(14), pp.89-102 (2014).
15. Khalili, J. and Alinezhad, A. "Performance evaluation in green supply chain using BSC, DEA and data mining", *International journal of supply and operations management*, **5**(2), pp.182-191 (2018).
16. Alinezhad, A. and Khalili, J., *MAUT Method. New methods and applications in multiple attribute decision making (MADM)*, Springer, Cham, pp. 127–131 (2019).
17. Amini, A. Alinezhad, A. and Yazdipoor, F., "A TOPSIS, VIKOR and DEA integrated evaluation method with belief structure under uncertainty to rank alternatives", *International Journal of Advanced Operations Management*, **11**(3), pp. 171-188 (2019).

18. Vaezi, E. “Performance Measurement in the Health Care Sector: a Leader-Follower Network DEA Model based on Double Frontier Analysis”, *Scientia Iranica*, (2020).
19. Esmaeeli, J., Amiri, M. and Taghizadeh, H. “A new approach in the DEA technique for measurement of productivity of decision-making units through efficiency and effectiveness”, *Scientia Iranica*, (2021).
20. Sadat Rezaei, M. and Haeri, A. “A heuristic method for choosing 'virtual best' DMUs to enhance the discrimination power of the augmented DEA model”, *Scientia Iranica*, **28**(4), pp. 2400-2418. (2021).
21. Emrouznejad, A. and Yang, G.L. “A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016”, *Socio-economic planning sciences*, **61**, pp.4-8 (2018).
22. Kao, C. “Network data envelopment analysis”, *International Series in Operations Research & Management Science*, **10**, pp.978-3 (2017).
23. Zhu, N., Zhu, C. and Emrouznejad, A. “A combined machine learning algorithms and DEA method for measuring and predicting the efficiency of Chinese manufacturing listed companies”, *Journal of Management Science and Engineering*, (2020).
24. Agrawal, T. “Hyperparameter Optimization in Machine Learning”, *Apress*, (2021).
25. Misiunas, N., Oztekin, A., Chen, Y., et al. “DEANN: A healthcare analytic methodology of data envelopment analysis and artificial neural networks for the prediction of organ recipient functional status”, *Omega*, **58**, pp.46-54 (2016).
26. De Clercq, D., Wen, Z. and Fei, F. “Determinants of efficiency in anaerobic bio-waste co-digestion facilities: A data envelopment analysis and gradient boosting approach”, *Applied Energy*, **253**, p.113570 (2019).
27. Liu, L. and Zhan, X. “Analysis of financing efficiency of Chinese agricultural listed companies based on machine learning”, *Complexity*, (2019).
28. Mirmozaffari, M., Boskabadi, A., Azeem, G., et al. “Machine learning clustering algorithms based on the DEA optimization approach for banking system in developing countries”, *European Journal of Engineering and Technology Research*, **5**(6), pp.651-658 (2020).
29. Rebai, S., Yahia, F.B. and Essid, H. “A graphically based machine learning approach to predict secondary schools performance in Tunisia”, *Socio-Economic Planning Sciences*, **70**, p.100724 (2020).
30. Salehi, V., Veitch, B. and Musharraf, M. “Measuring and improving adaptive capacity in resilient systems by means of an integrated DEA-Machine learning approach”, *Applied ergonomics*, **82**, p.102975 (2020).
31. Gupta, A., Kohli, M. and Malhotra, N. “Classification based on Data Envelopment Analysis and supervised learning: A case study on energy performance of residential buildings”, *In 2016 IEEE 1st international conference on power electronics, intelligent control and energy systems (ICPEICES)*, pp. 1-5 (2016).
32. Nandy, A. and Singh, P.K. “Farm efficiency estimation using a hybrid approach of machine-learning and data envelopment analysis: Evidence from rural eastern India”, *Journal of Cleaner Production*, **267**, p.122106 (2020).
33. Emrouznejad, A. and Shale, E. “A combined neural network and DEA for measuring efficiency of large scale datasets”, Computers & Industrial Engineering, **56**(1), pp.249-254 (2009).
34. Murphy, K.P. “Machine *learning: a probabilistic perspective*”, MIT press, (2012).
35. Loey, M., Manogaran, G., Taha, M.H.N., et al. “A hybrid deep transfer learning model with machine learning methods for face mask detection in the era of the COVID-19 pandemic”, *Measurement*, **167**, p.108288 (2021).
36. Ordu, M., Kirli Akin, H. and Demir, E. “Healthcare systems and Covid19: Lessons to be learnt from efficient countries”, *The International Journal of Health Planning and Management*, (2021).
37. Mariano, E., Torres, B., Almeida, M., et al. “Brazilian states in the context of COVID-19 pandemic: an index proposition using Network Data Envelopment Analysis”, *IEEE Latin America Transactions*, **19**(6), pp.917-924 (2021).
38. Nepomuceno, T.C., Silva, W., Nepomuceno, K.T., et al. “A DEA-based complexity of needs approach for hospital beds evacuation during the COVID-19 outbreak”, *Journal of healthcare engineering*, (2020).
39. Yeasmin, S., Banik, R., Hossain, S., et al. “Impact of COVID-19 pandemic on the mental health of children in Bangladesh: A cross-sectional study”, *Children and youth services review*, **117**, p.105277 (2020).
40. Ahamad, M.M., Aktar, S., Rashed-Al-Mahfuz, M., et al. “A machine learning model to identify early stage symptoms of SARS-Cov-2 infected patients”, *Expert systems with applications*, **160**, p.113661 (2020).
41. Malki, Z., Atlam, E.S., Hassanien, A.E., et al. “Association between weather data and COVID-19 pandemic predicting mortality rate: Machine learning approaches”, *Chaos, Solitons & Fractals*, **138**, p.110137 (2020).
42. Sonbhadra, S.K., Agarwal, S. and Nagabhushan, P. “Target specific mining of COVID-19 scholarly articles using one-class approach”, *Chaos, Solitons & Fractals*, **140**, p.110155 (2020).
43. Mahmoudi, M.R., Baleanu, D., Mansor, Z., et al. “Fuzzy clustering method to compare the spread rate of Covid-19 in the high risks countries”, *Chaos, Solitons & Fractals*, **140**, p.110230 (2020).

44. Imtyaz, A., Haleem, A. and Javaid, M. “Analysing governmental response to the COVID-19 pandemic”, *Journal of Oral Biology and Craniofacial Research*, **10**(4), pp.504-513 (2020).
45. Guerrero, M.D., Vanderloo, L.M., Rhodes, R.E., et al. “Canadian children's and youth's adherence to the 24-h movement guidelines during the COVID-19 pandemic: A decision tree analysis”, *Journal of sport and health science*, **9**(4), pp.313-321 (2020).
46. Mei, Y., Weinberg, S.E., Zhao, L., et al. “Risk stratification of hospitalized COVID-19 patients through comparative studies of laboratory results with influenza”, *E-Clinical Medicine*, **26**, p.100475 (2020).
47. Aydin, N. and Yurdakul, G. “Assessing countries’ performances against COVID-19 via WSIDEA and machine learning algorithms”, *Applied Soft Computing*, **97**, p.106792 (2020).
48. Institute for Health Metrics and Evaluation, COVID-19 Projections, 2021. URL https://covid19.healthdata.org/
49. Liu, W.B., Meng, W., Li, X.X., et al. “DEA models with undesirable inputs and outputs”, *Annals of Operations Research*, **173**(1), pp.177-194 (2010).
50. Färe, R. and Grosskopf, S. “Modeling undesirable factors in efficiency evaluation: comment”, *European Journal of Operational Research*, **157**(1), pp.242-245 (2004).
51. Kiani Mavi, R. Makui, A. Fazli, S., et al. “A forecasting method in data envelopment analysis with group decision making”, *International Journal of Applied Management Science*. **2** (2), pp. 152-168 (2010).
52. Färe, R. and Grosskopf, S. “Productivity and intermediate products: A frontier approach”, *Economics letters*, **50**(1), pp.65-70 (1996).
53. Kao, C. “Efficiency decomposition in network data envelopment analysis: A relational model”, *European journal of operational research*, **192**(3), pp.949-962 (2009).
54. Kumar, A. and Mayank, J., *Ensemble Learning for AI Developers*, New Delhi, India: Springer, (2020).
55. Zhou, Z.H., *Ensemble methods: foundations and algorithms*, Chapman and Hall/CRC, (2019).
56. Alfaro, E., Gámez, M. and García, N., *Ensemble classification methods with applications in R*, John Wiley & Sons, (2018).
57. Zhang, C. and Ma, Y., *Ensemble machine learning: methods and applications*, Springer Science & Business Media, (2012).
58. Breiman, L. “Bagging predictors”, *Machine learning*, **24**(2), pp.123-140 (1996).
59. Freund, Y. and Schapire, R.E. “Experiments with a new boosting algorithm”, *in icml*, **96**, pp. 148-156 (1996).
60. Seiffert, C., Khoshgoftaar, T.M., Van Hulse, J., et al. “RUSBoost: Improving classification performance when training data is skewed”, *19th International Conference on Pattern Recognition*, pp. 1-4, (2008).
61. Sarkis, J., *Preparing your data for DEA. In Modeling data irregularities and structural complexities in data envelopment analysis*, Springer, Boston, MA, pp. 305-320 (2007).
62. The Math Works, Inc., MATLAB, version R2019b, URL https://de.mathworks.com/
63. Tabachnick, B. G., Fidell, L. S. and Ullman, J. B., *Using multivariate statistics*, Vol. 5. Boston, MA: Pearson, (2007).
64. Cousineau, D. and Chartier, S. “Outliers detection and treatment: a review”, *International Journal of Psychological Research*, **3**(1), pp.58-67 (2010).
65. Kalkan, Ö. K., Yusuf, K. and Kelecioğlu, H. “Evaluating performance of missing data imputation methods in IRT analyses”, *International Journal of Assessment Tools in Education*, **5**(3), pp.403-416 (2018).

Author Biography

Ali Taherinezhad is currently M.Sc. Student in the field of Industrial Engineering - Systems Optimization in Qazvin Islamic Azad University (QIAU). He received his B.Sc. degree in the field of Industrial Engineering in 2019 from QIAU. His research interests are Mathematical Modeling, Data Analytics and Machine Learning.

Alireza Alinezhad received his B.Sc. degree in Applied Mathematics from Iran University of Science and Technology, M.Sc. degree in Industrial Engineering from Tarbiat Modarres University, and Ph.D. degree in Industrial Engineering, from Islamic Azad University, Science and Research Branch. He is currently an Associate Professor at the Department of Industrial Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran. His research interests are Data Envelopment Analysis (DEA), Multiple Criteria Decision Making (MCDM), and Quality Engineering.

Figure and Table Captions:

Figure 1. The research methodology outline.
Figure 2. An overview on COVID-19 crisis management systems.
Figure 3. The proposed two-stage DEA model for evaluating the countries' performance.
Figure 4. A common architecture of ensemble learning [55].
Figure 5. The Bagging algorithm.
Figure 6. The AdaBoost.M1 algorithm.
Figure 7. The RUSBoost algorithm [60].
Figure 8. The growth rate of total cases and currently infected worldwide (linear scale).
Figure 9. The classification approach of countries via the box plot of efficiency scores.
Figure 10. The box plot of features before and after removing outlier values. Center lines show the medians; box limits indicate the 25th and 75th percentiles as determined using MATLAB software [62]; whiskers extend 1.5 times the interquartile range from the 25th and 75th.
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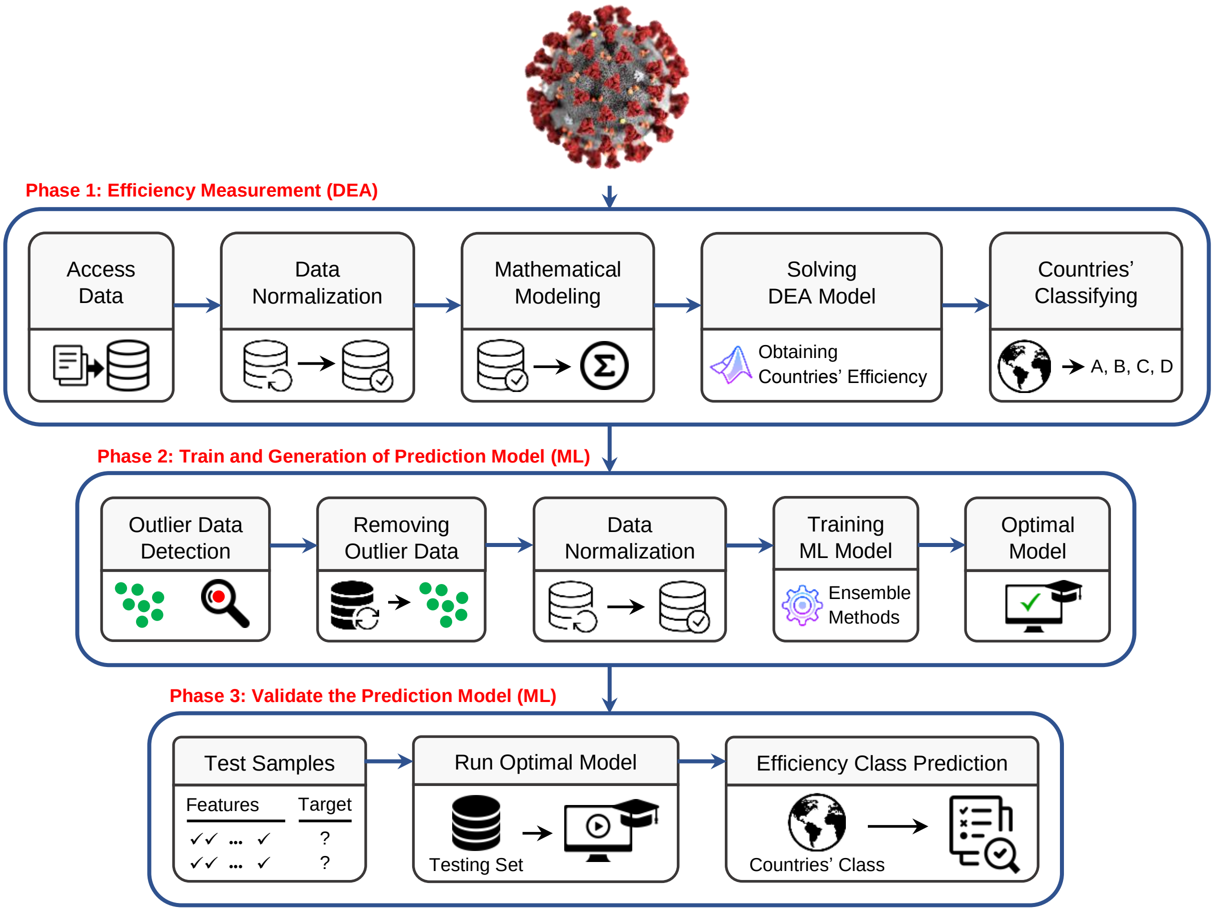
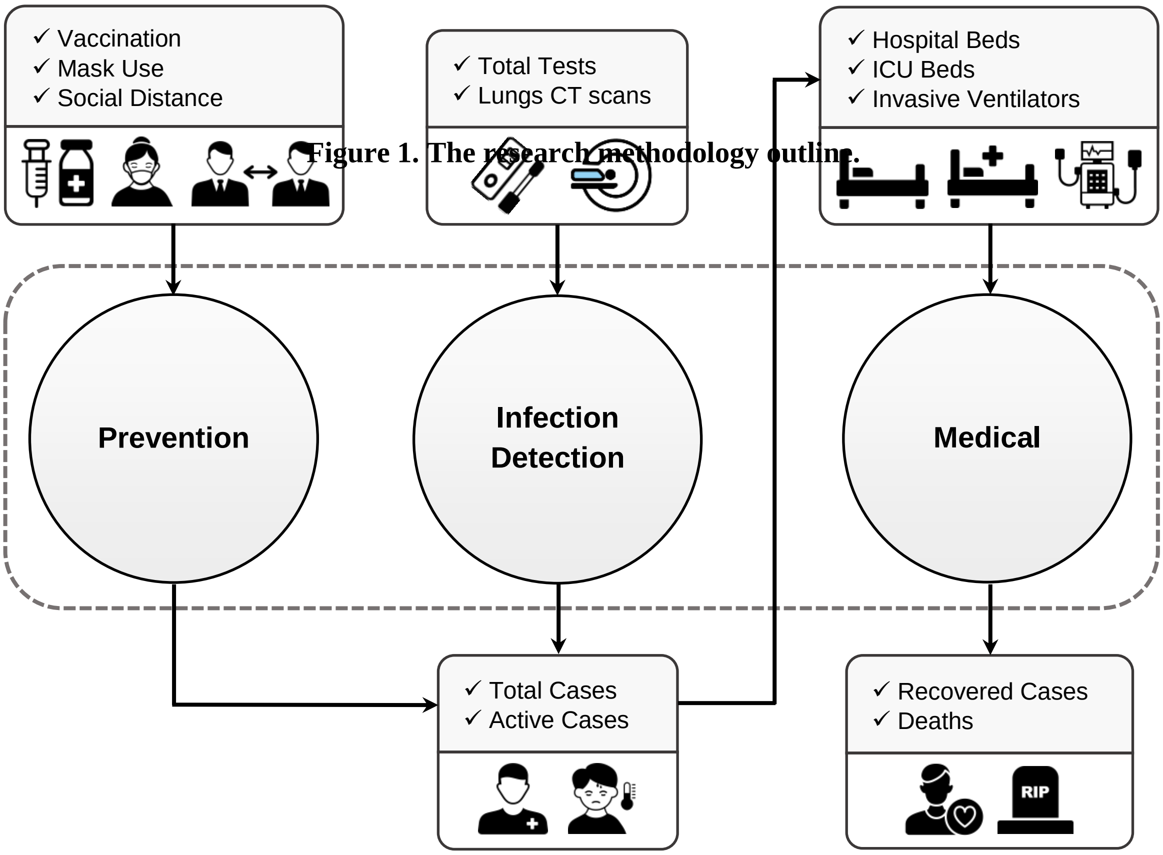
Table 3. The efficiency scores and countries' class.
Table 4. Statistical parameters of the dataset after removing outlier data.
Table 5. Prediction testing samples via the optimal ensemble model.





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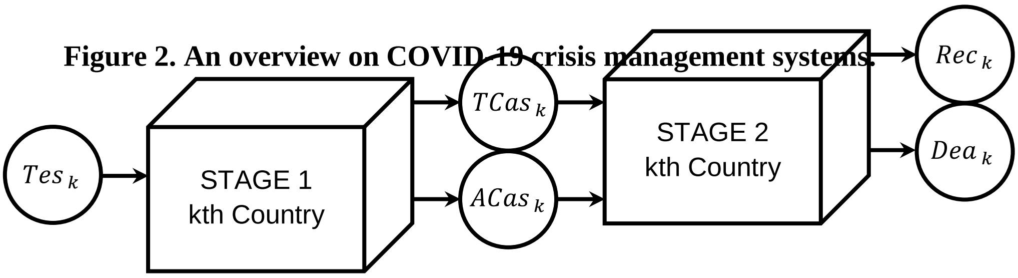


Figure 3. The proposed two-stage DEA model for evaluating the countries' performance.

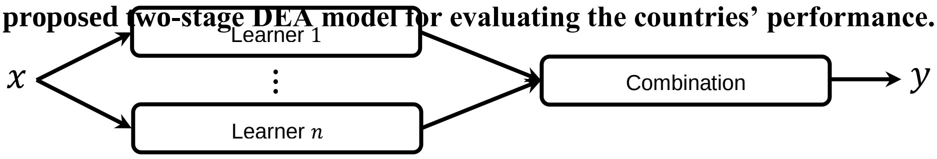


Figure 4. A common architecture of ensemble learning [55].

Input: Data set $\mathbf{D} = \{(\boldsymbol{x}_1, y_1), (\boldsymbol{x}_2, y_2), \ldots, (\boldsymbol{x}_m, y_m)\}$;

Base learning algorithm ω;

Number of base learners L.

Process:

1. for $l = 1, \ldots, L$:

2. $h_l = \omega(\mathbf{D}, d_{bs})$ $\%d_{bs}$ is the bootstrap distribution

3. end

Output: $H(\boldsymbol{x}) = \arg\max_{y \in Y} \sum_{l=1}^{L} \mathbb{I}\left(h_l(\boldsymbol{x}) = y\right)$

Figure 5. The Bagging algorithm.

Input: Data set $\mathbf{D} = \{(\boldsymbol{x}_1, y_1), (\boldsymbol{x}_2, y_2), \ldots, (\boldsymbol{x}_m, y_m)\}$;

Number of learning rounds L.

Process:

1. Start with $w_1(i) = 1/m$, $i = 1, 2, \ldots, m$. % Initialize the weight distribution

2. Repeat for $l = 1, 2, \ldots, L$.

a. Fit the classifier $c_l(\boldsymbol{x}_i) \in \{1, 2, \ldots, k\}$ using the weights $w_l(i)$ in $\mathbf{D}_l$.

b. Compute : $\varepsilon_l = \sum_{i=1}^{m} w_l(i) \, \mathbf{I} \, (c_l(\boldsymbol{x}_i) \neq y_i) Y \alpha_l = \ln \left(\frac{1-\varepsilon_l}{\varepsilon_l} \right)$. % Evaluate the error of c_l

c. Update the the weights $w_{l+1}(i) = w_l(i) \exp\left(\alpha_l \, \mathbf{I} \, (c_l(\boldsymbol{x}_i) \neq y_i)\right)$ and normalize them.

3. end

Output the final classifier: $C(\boldsymbol{x}_i) = \arg\max_{y \in Y} \sum_{l=1}^{L} \alpha_l \, \mathbf{I} \, (c_l(\boldsymbol{x}_i) = y_i)$

Figure 6. The AdaBoost.M1 algorithm.

Given: Set S of examples $(x_1, y_1), \ldots, (x_m, y_m)$ with minority class $y^r \in Y, |Y| = 2$

Weak learner, $WeakLearn$

Number of iterations, T

Desired percentage of total instances to be represented by the minority class, N

1. Initialize $D_1(i) = 1/m$ for all i.
2. Do for $t = 1, 2, \ldots, T$

   a. Create temporary training dataset S_t' with distribution D_t' using random undersampling

   b. Call $WeakLearn$, providing it with examples S_t' and their weights D_t'.

   c. Get back a hypothesis $h_t : X \times Y \rightarrow [0, 1]$.

   d. Calculate the pseudo - loss (for S and D_t) :

   $$\varepsilon_t = \sum_{(i,y): y_i \neq y} D_t(i)(1 - h_t(x_i, y_i) + h_t(x_i, y)).$$

   e. Calculate the weight update parameter :

   $$\alpha_t = \frac{\varepsilon_t}{1 - \varepsilon_t}.$$

   f. Update D_t :

   $$D_{t+1}(i) = D_t(i) \, \alpha_t^{\frac{1}{2}(1 + h_t(x_i, y_i) - h_t(x_i, y : y \neq y_i))}.$$

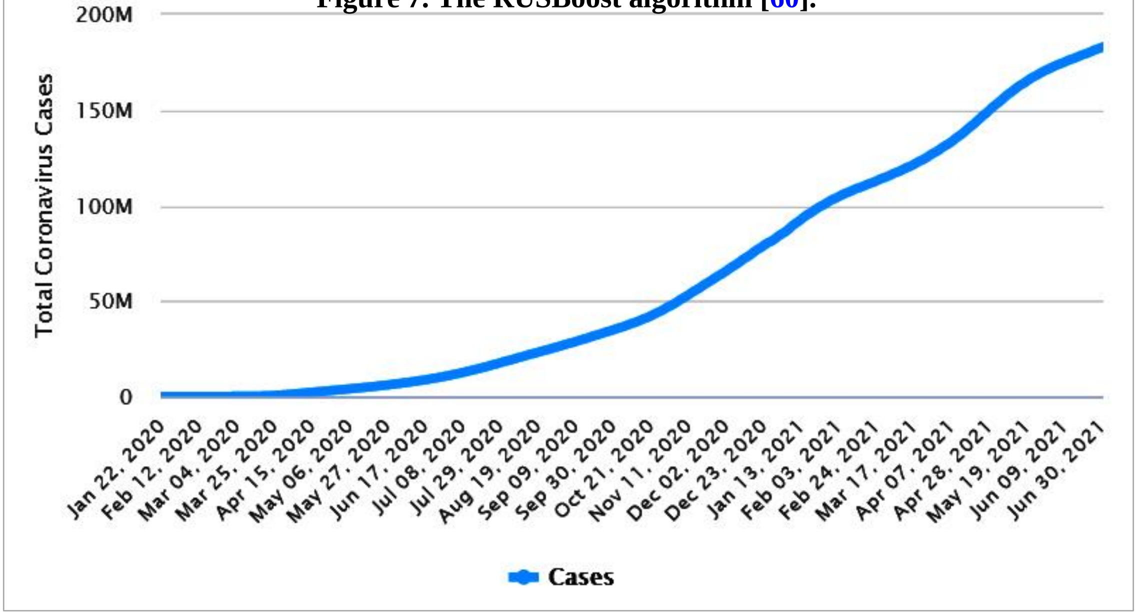
   g. Normalize D_{t+1} : Let $Z_t = \sum_i D_{t+1}(i)$.

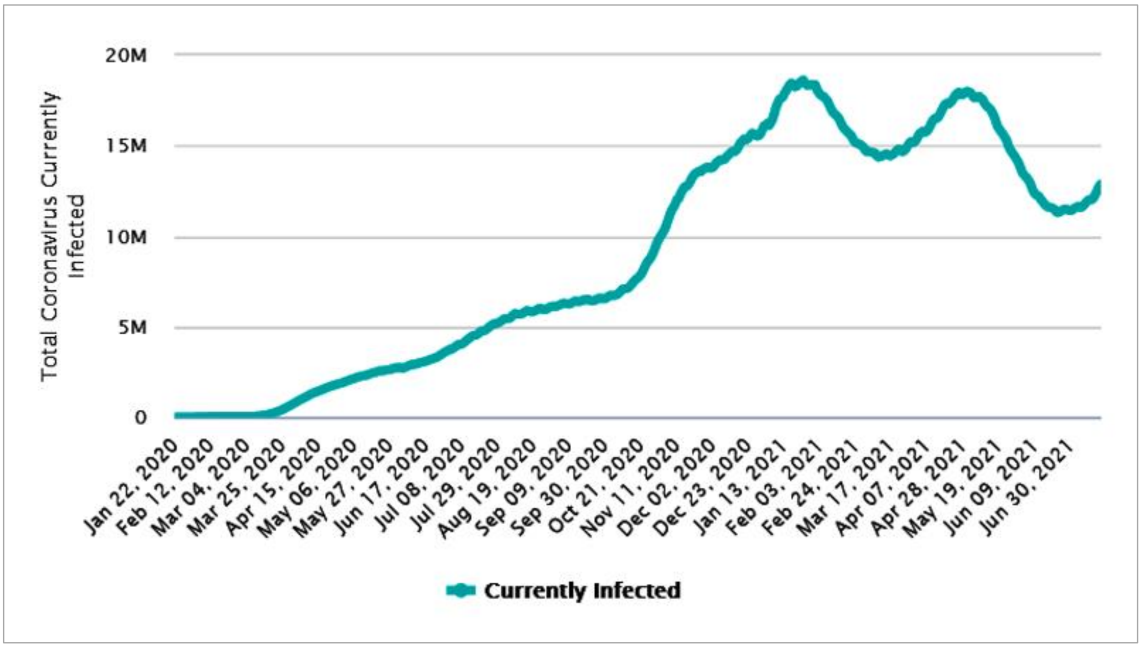
   $$D_{t+1}(i) = \frac{D_{t+1}(i)}{Z_t}.$$

3. Output the final hypothesis :

$$H(x) = \arg\max_{y \in Y} \sum_{t=1}^{T} h_t(x, y) \log \frac{1}{\alpha_t}.$$

Figure 7. The RUSBoost algorithm [60].





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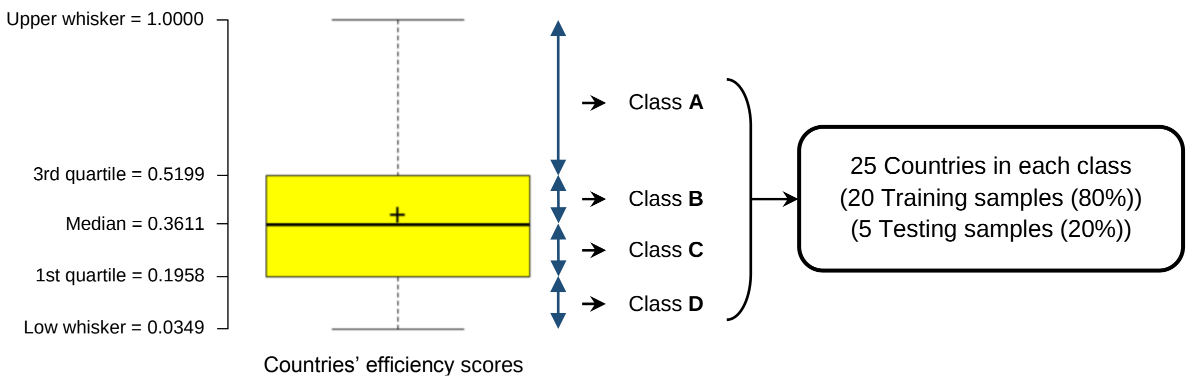

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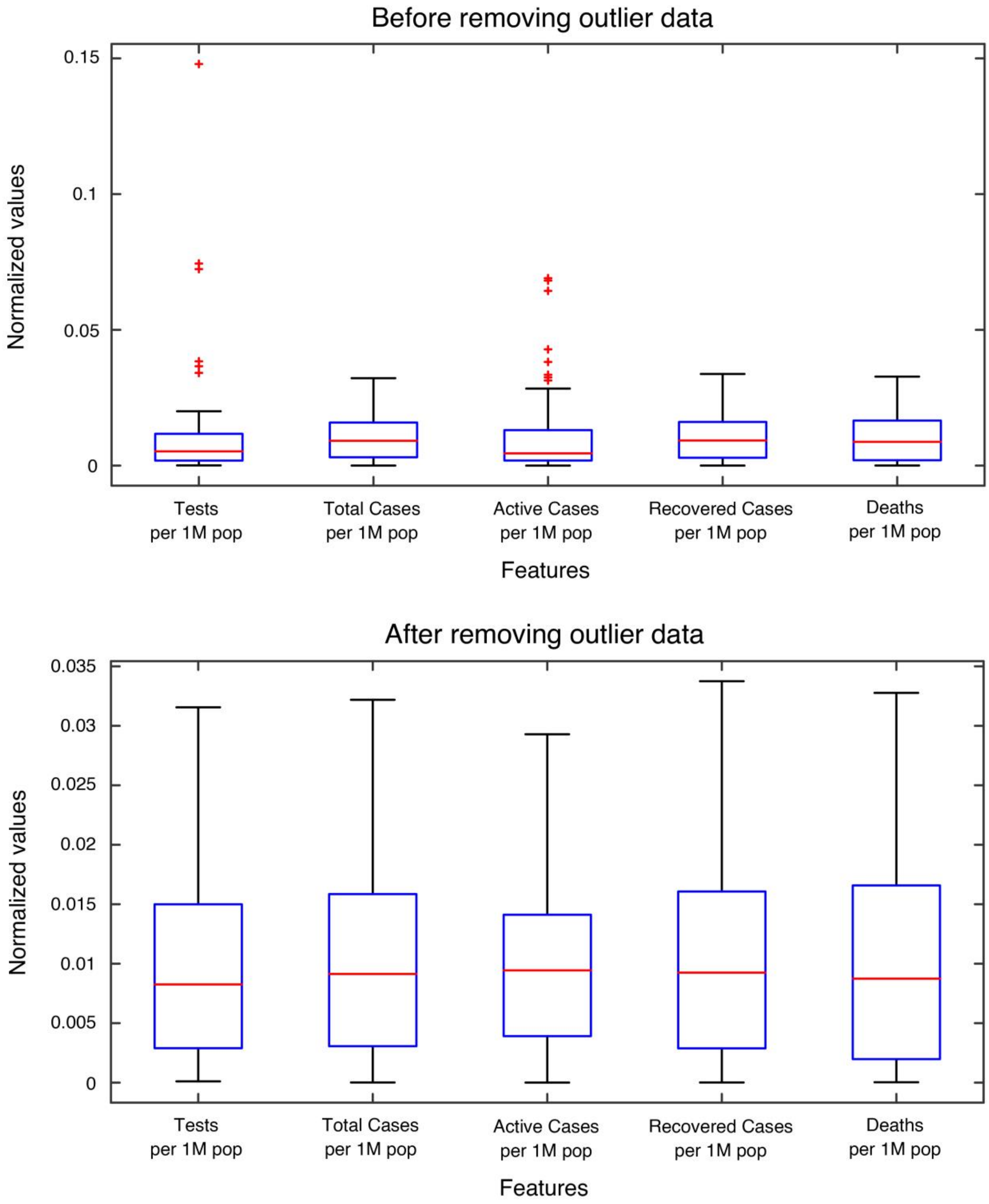

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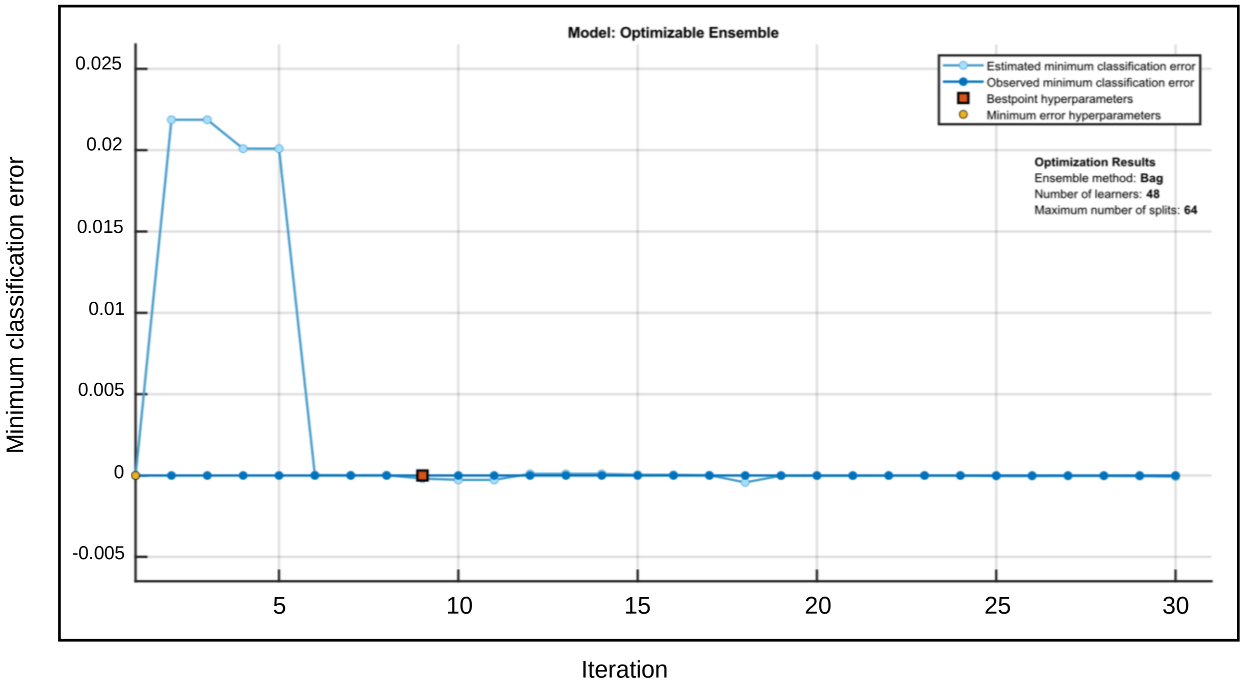

Figure 11. The minimum classification error plot.

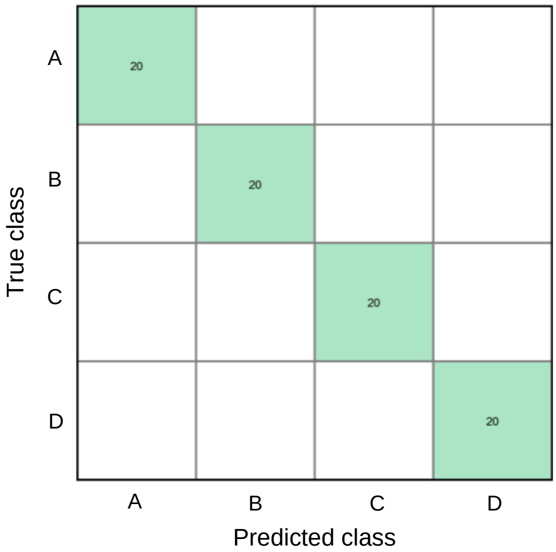

Figure 12. The confusion matrix of class prediction of training samples.

Table 1. A summary review on works related to this paper.

		Data Envelopment Analysis (DEA) Approach			Machine Learning (ML) Approach		Case Study
Research	**Year**	**DEA Based Modeling**	**Two-Stage DEA**	**Desirable-Undesirable Variables**	**ML Based Evaluating**	**Ensemble Learning Methods**	**COVID-19**
Loey et al. [35]	2021	×	×	×	✓	×	✓
Ordu et al. [36]	2021	✓	×	×	×	×	✓
Mariano et al. [37]	2021	✓	✓	×	×	×	✓
Nepomuceno et al. [38]	2020	✓	✓	×	×	×	✓
Yeasmina et al. [39]	2020	×	×	×	✓	×	✓
Ahamad et al. [40]	2020	×	×	×	✓	×	✓
Malki et al. [41]	2020	×	×	×	✓	×	✓
Sonbhadra et al. [42]	2020	×	×	×	✓	×	✓
Mahmoudi et al. [43]	2020	×	×	×	✓	×	✓
Imtyaz et al. [44]	2020	×	×	×	✓	×	✓
Guerrero et al. [45]	2020	×	×	×	✓	×	✓
Mei et al. [46]	2020	×	×	×	✓	×	✓
Aydin and Yurdakul [47]	2020	✓	×	×	✓	×	✓
This research		✓	✓	✓	✓	✓	✓

Table 2. Descriptive statistics of the dataset.

Variable	N	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3	Maximum
Tests	100	763363	139710	1397097	5175	137589	399647	913662	11291690
Total cases	100	49504	3801	38008	64	15067	45236	78581	159346
Active cases	100	2238	306	3057	0.4	412	1009	2967	15451
Recovered cases	100	46317	3688	36880	60	13142	42834	74716	156316
Deaths	100	948.7	82.4	824.1	3.0	181.8	829.5	1592.5	3109.0

N, Number of samples; SE Mean, Standard Error Mean; StDev, Standard Deviation; Q, Quartile.

Table 3. The efficiency scores and countries' class.

k	Country	$\phi_k^{Relational^*}$	Efficiency score	Efficiency class	k	Country	$\phi_k^{Relational^*}$	Efficiency score	Efficiency class
1	United States	1.7589	0.5685	A	**51**	Slovakia	2.2338	0.4477	B
2	India	4.1745	0.2395	C	**52**	Tunisia	5.2792	0.1894	D
3	Brazil	2.0443	0.4892	B	**53**	Croatia	1.7779	0.5625	A
4	France	1.7735	0.5639	A	**54**	Georgia	1.7059	0.5862	A
5	Turkey	2.0151	0.4963	B	**55**	Uruguay	1.6103	0.6210	A
6	Russia	4.3505	0.2299	C	**56**	Costa Rica	2.7427	0.3646	B
7	United Kingdom	2.4073	0.4154	B	**57**	Kuwait	1.4312	0.6987	A
8	Argentina	1.7858	0.5600	A	**58**	Azerbaijan	3.4840	0.2870	C
9	Italy	2.2869	0.4373	B	**59**	Dominican Republic	3.9907	0.2506	C
10	Colombia	2.1349	0.4684	B	**60**	Palestine	2.3278	0.4296	B
11	Spain	1.9908	0.5023	B	**61**	Denmark	1.0000	1.0000	A
12	Germany	3.4181	0.2926	C	**62**	Guatemala	7.9905	0.1251	D
13	Iran	4.4962	0.2224	C	**63**	Lithuania	1.5185	0.6585	A
14	Poland	2.1756	0.4596	B	**64**	Egypt	28.6661	0.0349	D
15	Mexico	9.9883	0.1001	D	**65**	Ethiopia	5.7888	0.1727	D
16	Ukraine	2.9776	0.3358	C	**66**	Ireland	2.8813	0.3471	C
17	Indonesia	11.4102	0.0876	D	**67**	Bahrain	1.0000	1.0000	A
18	South Africa	5.3182	0.1880	D	**68**	Venezuela	4.5148	0.2215	C
19	Netherlands	1.5652	0.6389	A	**69**	Slovenia	1.2712	0.7867	A
20	Czechia	1.0268	0.9739	A	**70**	Moldova	2.4160	0.4139	B
21	Chile	2.0034	0.4992	B	**71**	Honduras	14.8782	0.0672	D
22	Canada	3.8082	0.2626	C	**72**	Oman	2.7833	0.3593	C
23	Philippines	6.7864	0.1474	D	**73**	Sri Lanka	4.7445	0.2108	C
24	Iraq	3.5193	0.2841	C	**74**	Armenia	2.0533	0.4870	B
25	Sweden	1.4439	0.6926	A	**75**	Thailand	3.0195	0.3312	C
26	Romania	2.7550	0.3630	B	**76**	Qatar	1.0000	1.0000	A
27	Belgium	1.7599	0.5682	A	**77**	Bosnia and Herzegovina	2.8341	0.3528	C
28	Pakistan	9.0906	0.1100	D	**78**	Libya	4.2926	0.2330	C
29	Portugal	1.8667	0.5357	A	**79**	Kenya	10.1938	0.0981	D
30	Bangladesh	6.3506	0.1575	D	**80**	Cuba	2.6920	0.3715	B
31	Hungary	2.0479	0.4883	B	**81**	Nigeria	3.4743	0.2878	C
32	Japan	7.0847	0.1411	D	**82**	North Macedonia	2.1727	0.4603	B
33	Jordan	2.0535	0.4870	B	**83**	South Korea	4.9051	0.2039	C
34	Serbia	1.7851	0.5602	A	**84**	Myanmar	8.8709	0.1127	D
35	Switzerland	1.9031	0.5255	A	**85**	Latvia	2.0851	0.4796	B
36	Malaysia	2.6309	0.3801	B	**86**	Algeria	13.9735	0.0716	D
37	Austria	1.9872	0.5032	B	**87**	Albania	3.2115	0.3114	C
38	Nepal	4.6989	0.2128	C	**88**	Estonia	1.5275	0.6547	A
39	United Arab Emirates	1.1081	0.9024	A	**89**	Zambia	5.6516	0.1769	D
40	Lebanon	1.8873	0.5299	A	**90**	Norway	3.3097	0.3021	C
41	Morocco	6.0069	0.1665	D	**91**	Kyrgyzstan	5.5490	0.1802	D
42	Saudi Arabia	6.1104	0.1637	D	**92**	Uzbekistan	2.2792	0.4388	B
43	Ecuador	6.3480	0.1575	D	**93**	Afghanistan	24.3811	0.0410	D
44	Bolivia	5.1791	0.1931	D	**94**	Montenegro	1.0000	1.0000	A
45	Bulgaria	2.7449	0.3643	B	**95**	Mongolia	2.6082	0.3834	B
46	Greece	3.8262	0.2614	C	**96**	Ghana	2.8683	0.3486	C
47	Belarus	2.1539	0.4643	B	**97**	Finland	7.8293	0.1277	D
48	Kazakhstan	3.9300	0.2545	C	**98**	China	1.0000	1.0000	A
49	Paraguay	3.1497	0.3175	C	**99**	Cameroon	5.9516	0.1680	D
50	Panama	1.7351	0.5763	A	**100**	El Salvador	8.8150	0.1134	D

Table 4. Statistical parameters of the dataset after removing outlier data.

Variable	N	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3	Maximum
Tests	100	484120	40178	401779	5175	137589	399647	736530	1527618
Total cases	100	49504	3801	38008	64	15067	45236	78581	159346
Active cases	100	1069.0	80.4	803.9	0.4	411.5	1009.0	1509.1	3131.0
Recovered cases	100	46317	3688	36880	60	13142	42834	74716	156316
Deaths	100	948.7	82.4	824.1	3.0	181.8	829.5	1592.5	3109.0

N, Number of samples; SE Mean, Standard Error Mean; StDev, Standard Deviation; Q, Quartile.

Table 5. Prediction testing samples via the optimal ensemble model.

Row	Country	True class	Predicted class	Correct prediction
1	United States	A	A	✓
2	India	C	C	✓
3	Brazil	B	B	✓
4	France	A	A	✓
5	Turkey	B	B	✓
6	Russia	C	C	✓
7	United Kingdom	B	B	✓
8	Argentina	A	A	✓
9	Italy	B	B	✓
10	Spain	B	B	✓
11	Germany	C	C	✓
12	Iran	C	C	✓
13	Mexico	D	D	✓
14	Ukraine	C	C	✓
15	Indonesia	D	D	✓
16	South Africa	D	C	×
17	Netherlands	A	A	✓
18	Czechia	A	A	✓
19	Philippines	D	D	✓
20	Pakistan	D	D	✓