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Sensitivity Analysis by the PROMETHEE-GAIA method: Algorithms evaluation for COVID-19 prediction

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Abstract

With the expansion of coronavirus in the World, the search for technology solutions based on the analysis and prospecting of diseases has become constant. The paper addresses a machine learning algorithms analysis used to predict and identify infected patients. For analysis, we use a multicriteria approach using the PROMETHEE-GAIA method, providing the structuring of alternatives respective to a set of criteria, thus enabling the obtaining of their importance degree under the perspective of multiple criteria. The study approaches a sensitivity analysis, evaluating the alternatives using the PROMETHEE I and II methods, along with the GAIA plan, both implemented by the Visual PROMETHEE computational tool, exploring numerical and graphical resources. The analysis model proves to be effective, guaranteeing the ranking of alternatives by inter criterion evaluation and local results with intra criterion evaluation, providing a transparent analysis concerning the selection of prediction algorithms to combat the COVID-19 pandemic.

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Keywords: Predicition Algorithms; COVID-19; Multiple Criteria Decision Analysis; PROMETHEE method.

1. Introduction

Regarding the expansion of the new coronavirus disease (SARS-CoV-2), the search for alternative solutions motivated the development of studies in the most diverse areas of science, in search of providing knowledge that would make prevention, prediction, and consequently the minimization and control of the COVID-19 pandemic

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[1]. In this scenario, recent researches based on Machine Learning (ML) and Artificial Intelligence (AI) presented these areas as promising technologies to support the challenges in healthcare during the outbreak [2].

As introduced, ML have been providing evaluation and prediction models as an aid for the identification of the cases [3]. As exposed in [4], ML can be understanding as data analyzing method, that provides computer update or adapt their actions concerning the prediction about any event or controlling machine. Performing a predictive algorithm for data evaluation related to patients under observation, it is possible to reduce the time required for the final diagnosis from the moment that given a diagnosis of positive infection, isolation and early treatment of disease can be provided [5].

Although, based on the described context, for effective implementation of a predictive algorithm, it is necessary to consider the performance of these technologies according to the set of metrics. Regarding this case, a multicriteria approach, an Operational Research field, would provide the structuring of these algorithms according to their respective metrics, making it possible to identify the most favorable set of algorithms for implementation in the given case [6].

The implementation of Multiple Criteria Decision Analysis (MCDA) supports studies related to the fight against the COVID-19 pandemic [7]. MCDA methods present technics that allow the structuring and understanding of a problem in complex environments [8], establish the preferences between the alternatives under multiples criteria, which are usually conflicting, assisting in the obtaining of solution for choice, ranking, sorting, and portfolio problematics [9].

Concerning the scenario presented, the study aims to provide an evaluation approach of prediction algorithms to support the identification of infection cases resulted from the virus contagion. To support the analysis is implemented the MCDA method PROMETHEE-GAIA [10], carrying out a sensitivity analysis approach from results and exploring graphical sources [11], enabling a ranking of the algorithms according to their respective performance in the evaluation criteria, providing a favorable set to implementation.

The paper is structured into four sessions. After the introduction, section 2 presents the axiomatic modeling of the PROMETHEE method and GAIA plan, followed by its sensitivity analysis approach. Section 3 explores the study case, defining alternatives and criteria in detail, then exposing all steps related to the method implementation, along with its computation software, related to algorithms prediction analysis for support COVID-19 pandemic. Section 4 concludes the study, exposing the gains of the approaching and proposal for future works.

2. PROMETHEE Method

The PROMETHEE method is based on a pairwise comparison evaluation between the alternatives belonging to the set A, being necessary for the decision-maker to indicate some attributes, as preference functions, thresholds, and criteria weights [12]. The process starts defining the performance of alternatives in each criterion, as maximization function $P_d(a_1, a_2) = f(a_1) - f(a_2)$ or minimization function $P_d(a_1, a_2) = f(a_2) - f(a_1)$.

The value $P_d(a_1, a_2)$ represents the performance of a_1 over a_2, and a preference function needs to be defined for an equivalent evaluation between the criteria, establishing an interval [0,1] for eachP_d. As presented in [13], can be used six types of generalized functions, but it is not exhaustive. According to each function, may be requested a preference (p) or indifference (q) threshold. Figure 1 exposes the six preference functions.

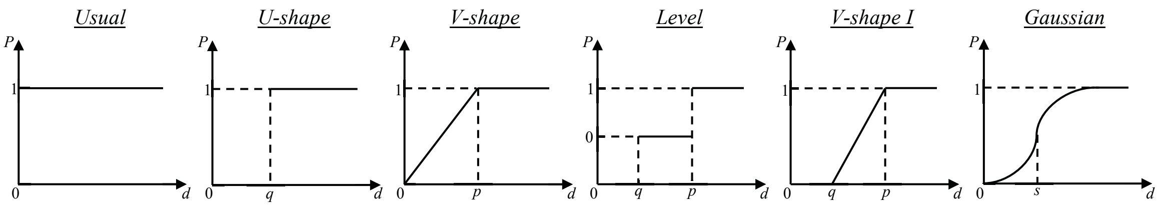

Fig. 1. Preference functions of PROMETHEE method, adapted from [13]

Normalized the performance of the alternatives, it is necessary to indicate the criteria weights, representing the preference or the importance of each criterion in the analysis. In the end, is obtained a Preference Global Index (1), enabling to generate the outranking flows, representing the performance of each alternative regarding the other in the problem context.

$$\pi(a_1, a_2) = \sum_{j=1}^{k} P_j(a_1, a_2) w_j \quad (1)$$

The positive flow ϕ^+ (2) represents how *a* outranks the other alternatives *x* in the set *A*, and the negative flow ϕ^- (3) represents how *a* is outranked by the other alternatives *x*. Both outranking flows are used in the PROMETHEE I method, how higher be the positive flow and lower be the negative flow, better is the alternative [10]. Also, a net outranking flow ϕ (4) is performed, particularly in the PROMETHEE II method, representing the difference between the positive and negative flows, obtaining a complete ranking.

$$\phi^+(a) = \frac{1}{n-1} \sum_{x \in A} \pi(a, x) \quad (2)$$

$$\phi^-(a) = \frac{1}{n-1} \sum_{x \in A} \pi(x, a) \quad (3)$$

$$\phi(a) = \phi^+(a) - \phi^-(a) \quad (4)$$

2.1. PROMETHEE-GAIA

Geometrical Analysis for Interactive Aid (GAIA), proposed by Brans and Mareschal [14], features a graphical resource as a decision aid. The GAIA plan has as basis the assumption that each alternative *a* is not characterized by the values of criteria but by a vector of mono-criteria flows, where $S_i(a_1), i = 1,2, \dots, k$, defined by the equation (5).

$$S_i(a_1) = \frac{1}{n-1} \sum_{j=1} [P_j(a_1, a_2) - P_j(a_2, a_1)] \quad (5)$$

Each alternative can be represented in a k-dimensional vector space by an R^k vector (6):

$$q_i = [(S_1(a_i), S_2(a_i), \dots, S_k(a_n))] \quad (6)$$

2.2. Sensitivity Analysis Approach

In search to provide a robustness analysis, we suggest the integration of three methodological analyses: PROMETHEE I, PROMETHEE II, and the GAIA plan. The partial and complete outranking will provide an inter criterion analysis, representing the global performance of alternatives. On the other hand, the geometrical analysis of the GAIA plan will provide a better understanding of alternatives performances in each criterion and its influence on the problem in analysis. The simultaneous application of the three methodologies to the data in evaluation allows at the same time to make a sensitivity analysis comparing the suggestions [15,16]. Figure 2 exposes the axiomatic structure of the Sensitivity Analysis Approach.

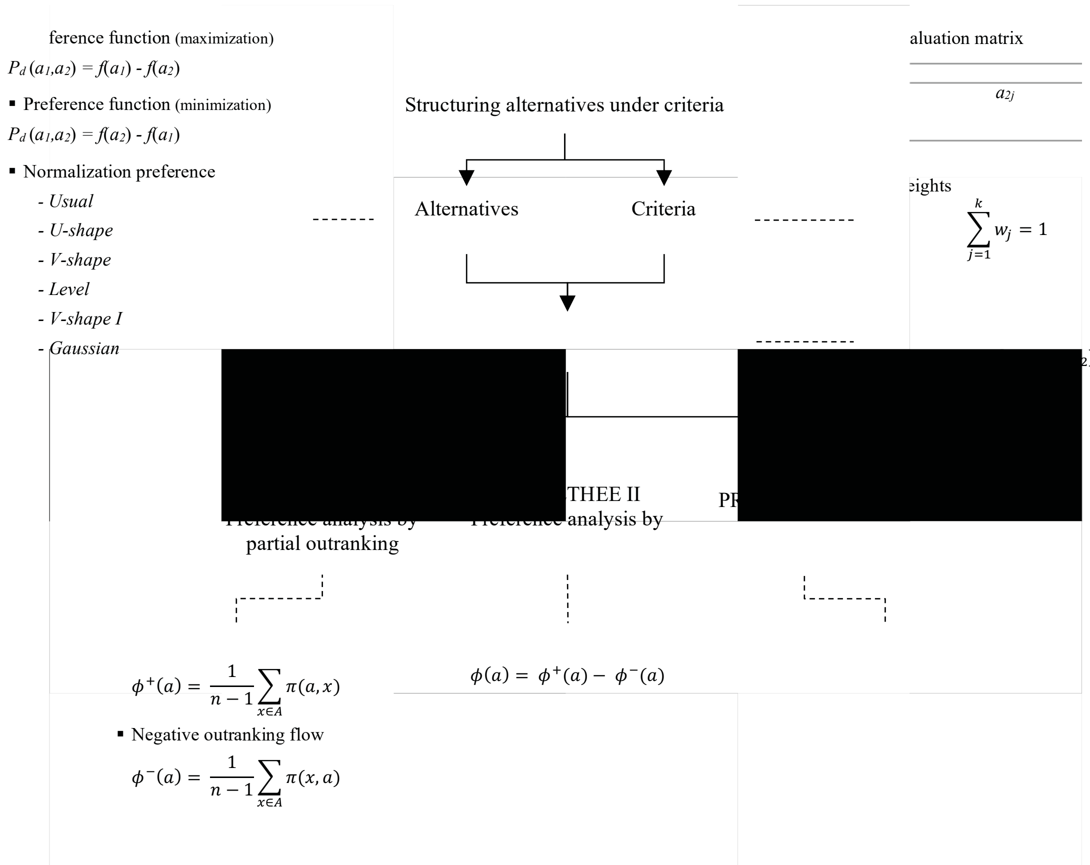

Fig. 2. Axiomatic structuring of Sensitivity Analysis Approach by the PROMETHEE-GAIA method

3. Study Case

The case in analysis approaches the evaluation of prediction algorithms as a way to support researches and predictive models related to COVID-19, by the moment that an effective implementation can be helpful to determine if a person is infected with the virus or not, and indirectly, provide to estimate the number of cases in a given region [17].

In this scenario, addressing a multicriteria evaluation was analyzed a dataset, enabling to analyze a set of algorithms, allowing to determine the performance of each algorithm in each type of metric. Were realized individuals experiments with different algorithms using the R software, in search to obtain the most suitable model for the analysis and eliminate poorly performing alternatives, where was established a set of ten models: Logistic Regression, Random Forest, Gradient Boosting, XGBoost, MLP, LDA, KNN, SVM Radial, C5.0, and QDA.

Considering the set of alternatives, the metrics analyzed enabled to make the structure a set of seven criteria. The established criteria provide an individual analysis as to the positive and negative classification of the algorithms, in other words, and in the context of COVID-19, are used the metrics to provide an assertiveness degree that classifies a given patient as being or not infected by the virus. Below is described each criterion.

- *Area Under de ROC Curve (AUC)*: Calculated from the ROC curve (Receiver Operating Characteristic), the AUC is the value of the area under the ROC curve, where, as closer, the degree is to 1, greater is the ability of the model to distinguish positive and negative classes;
- *Accuracy*: Overall rate of correct classifications, however, has the disadvantage of its inability to distinguish the types of errors (false positives or false negatives) made by the model;
- *Kappa*: Indicates the agreement between observed and classified data, where the closer to 0 indicates that there is no agreement and the closer to 1 indicates perfect agreement;
- *Sensitivity*: Rate of correct classifications among the really positive samples, where as highest is the values, is indicated the low occurrence of false negatives;
- *Specificity*: Rate of correct classifications among the really negative samples, where as highest is the values, is indicated the low occurrence of false positives;
- *Positive Predictive Value* (*PPV*): Rate of correct classifications among samples classified as positive, where as highest is the values, is indicated the low occurrence of false-positive;
- *Negative Predictive Value* (*NPV*): Rate of correct classifications among samples classified as negative, where as highest is the values, is indicated the low occurrence of false-negative.

For a better understanding of the last four criteria described, figure 3, based on a confusion matrix [18], exposes the relation between the metrics related to the observed and predicted event. In this case, the Sensitivity metric presents a better assertiveness regarding positive cases, and the Specificity presents a better assertiveness concerning negative cases. Considering the evaluation of COVID-19 cases, it is essential to prioritize the Specificity and correlated criteria from the moment that low performance in this metric can induce the indication of an infected patient as a healthy patient (false positive) [19].

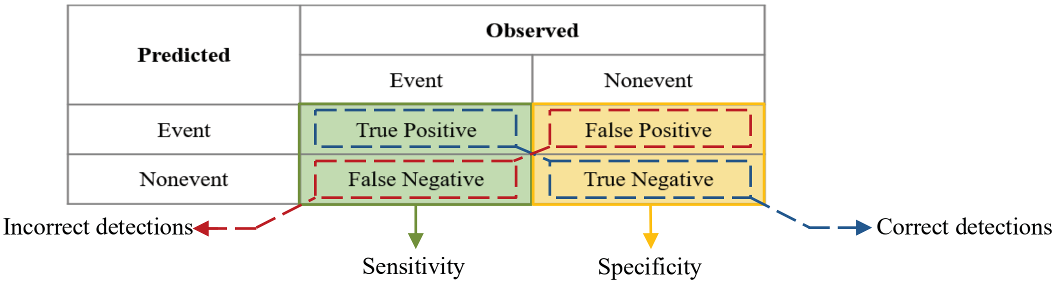

Fig. 3. Axiomatic structuring of Sensitivity Analysis Approach by the PROMETHEE-GAIA method

Considering the presence of tradeoff between the of algorithms, table 1 exposes the decision matrix.

Table 1. Evaluation matrix of prediction algorithms

	AUC	*Accuracy*	*Kappa*	*Sensitivity*	*Specificity*	*PPV*	*NPV*
Logistic Regression	0.8091	0.8068	0.6147	0.8508	0.7673	0.7667	0.8512
Random Forest	0.8982	0.8943	0.7898	0.9708	0.8257	0.8335	0.9692
Gradient Boosting	0.8362	0.8351	0.6702	0.8567	0.8156	0.8068	0.8636
XGBoost	0.8443	0.8429	0.6860	0.8711	0.8175	0.8110	0.8759
MLP	0.8292	0.8277	0.6558	0.8569	0.8014	0.7950	0.8617
LDA	0.7996	0.7971	0.5956	0.8459	0.7533	0.7550	0.8447
KNN	0.8384	0.8378	0.6754	0.8484	0.8284	0.8163	0.8587
SVM Radial	0.8265	0.8243	0.6494	0.8675	0.7854	0.7842	0.8684
C5.0	0.8588	0.8590	0.7173	0.8563	0.8613	0.8473	0.8696
QDA	0.7762	0.7692	0.5440	0.9066	0.6457	0.6970	0.8850

3.1. Numerical Implementation

For the implementation process, was used the Visual PROMETHEE software [20], providing to perform the method and have a graphical analysis from results.

With the establishment of the numerical data, all criteria were set as a monotonic benefit (maximization), whereas higher is the performance, better is the alternative. In search to define the preference degree, was determined the preference function *V-shape* to the normalization procedure, providing to establish a preference threshold for each criterion. Considering that all data set is sensitive to any difference present between the variables, the V-shape function becomes suitable for the problematic. Table 2 exposes the described data.

For criteria weights, was used a five-point scale to determine the respective preferences, where 5 represents a variable with high importance, and 1 expose low importance. Table 2 presents the established weights and normalized weights, determining the relative importance of each criterion, where the criteria *AUC*, *Sensitivity*, and *NPV* present the highest importance, from the moment that these criteria are responsible for determining the effectiveness of a given algorithm.

Table 2. Cardinal preferences of evaluation

	Generalized Function	*Preference Function*	*Preference threshold (p)*	*Weights*	*Normalized Weights*
AUC	*maximization*	*V-shape*	0.0610	5	0.22
Accuracy	*maximization*	*V-shape*	0.0626	1	0.04
Kappa	*maximization*	*V-shape*	0.1229	1	0.04
Sensitivity	*maximization*	*V-shape*	0.0624	5	0.22
Specificity	*maximization*	*V-shape*	0.1078	3	0.13
PPV	*maximization*	*V-shape*	0.0752	3	0.13
NPV	*maximization*	*V-shape*	0.0622	5	0.22

Once implemented the method, are obtained the preference global index between the alternatives, making it possible to determine the positive, negative, and net outranking flows. As exposed in table 3, the positive flow represents how outranks an alternative regarding the other, and the negative flow how was outranked thus, providing the partial preference analysis by the PROMETHEE I method. Also, table 3 exposes the net flows, representing the difference between positive and negative flows, as higher is the value, better is the alternative, and these degrees provide the complete preference analysis, represented by the PROMETHEE II method.

Table 3. Alternatives outranking flows

	Positive outranking flow	Negative outranking flow	Net outranking flow
Logistic Regression	0.0701	0.4073	-0.3372
Random Forest	0.8716	0.0045	0.8671
Gradient Boosting	0.2115	0.1702	0.0413
XGBoost	0.3003	0.1229	0.1774
MLP	0.1637	0.2174	-0.0537
LDA	0.0427	0.5168	-0.4741
KNN	0.2283	0.1712	0.0571
SVM Radial	0.1645	0.2351	-0.0706
C5.0	0.4381	0.0900	0.3481
QDA	0.1334	0.6888	-0.5554

3.2. Results Analysis

As explored in the previous sections, the worked approach represents the integration of PROMETHEE I, II, and the GAIA model, enabling the manipulation of preferences in different models.

The first analysis is based on the PROMETHEE I method, performing the positive and negative flows. As presented in figure 4, the algorithm Random Forest presented the best performance, sustaining the highest positive and lowest negative degree, preceded by C5.0 and XGBoost. The alternative KNN regarding Gradient Boosting and MLP concerning SVM Radial presented an incomparability relation respectively by the moment that one variable presented the highest positive flow, but the highest negative flow as well. The algorithm Logistic Regression becomes preferable to LDA, but both them sustained as incomparable regarding the QDA.

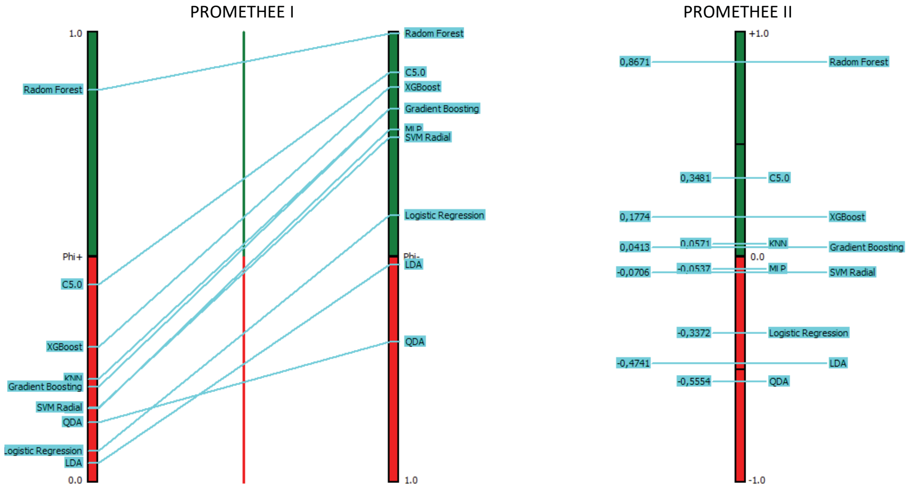

Fig. 4. Partial and complete preference analysis by the PROMETHEE I and II methods

The second analysis sustains a complete preference, making it possible to obtain a final ranking of alternatives and erase the incomparability relations. As exposed in figure 4 and related to the case, the algorithm Radom Forest remained the most favorable, being preceded by C5.0, XGBoost, KNN, Gradient Boosting, MLP, SVM Radial, logistic regression, LDA, QDA, in this order respectively.

In search of robustness analysis, is evaluated the GAIA methodology. In this model, by a graphical representation, it is possible to identify the performance of alternatives specifically on each criterion, performing an intra criterion analysis of the problem. Figure 5 highlights the performance of Radom Forest regarding the *Sensitivity* and *NPV* metrics, while C5.0, XGBoost, and KNN presented a regular performance concerning these two metrics, but a good performance in the other metrics in analysis. This analysis becomes useful from the moment that, having the impossibility of implementing an alternative, the evaluation of a solution in a specific criterion can generate influence in the final decision.

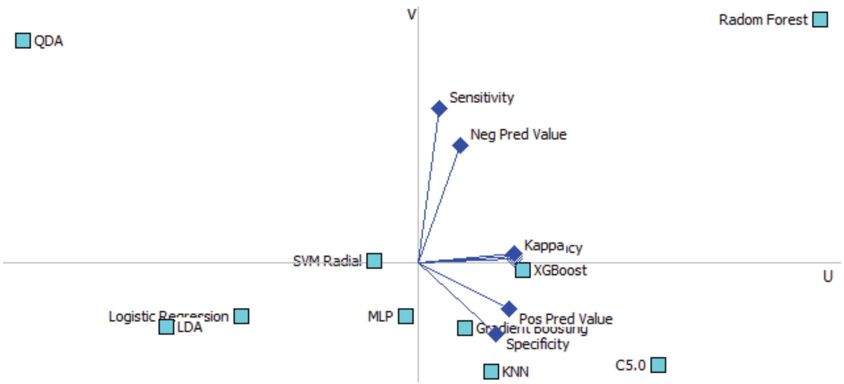

Fig. 5. GAIA plan analysis

The realized procedure provided a better understanding of the problem, along with the identification of a set of viable algorithms to support predictive analysis, but as important to define the favorable solution, by the final ranking made it possible to identify unfavorable models for implementation.

4. Conclusion

The paper aimed to explore viable alternatives to support the COVID-19 pandemic. As a methodological approach, we used the PROMETHEE-GAIA method to analyze ML algorithms as a case prediction model. The analysis sustained an integration of the PROMETHEE I, II, and GAIA plan, making it possible to manipulate the data in different evaluation models. The approach enabled an effectiveness analysis, providing to evaluate the problematic transparently, highlighting the criteria preferences, and enabling the ranking of alternatives.

The Visual PROMETHEE software was helpful for the procedure analysis implementation of study case, requiring only to structure the data and preferences into the computational tool, making it possible to explore the results through numerical and graphical exposition, supporting the inter criterion analysis by preference analysis, and an intra criterion performance of GAIA methodology.

It concludes that ML has been a helpful technology to support prediction analysis related to COVID-19 pandemic and multicriteria approaches, as the PROMETHEE methods, being useful to structuring and transparent assessment of complex problems. For future works, we suggest the implementation of the approach for other technologies that can serve as an aid in the fight against COVID-19.

References

[1] S. Lalmuanawma, J. Hussain, L. Chhakchhuak, Applications of machine learning and artificial intelligence for Covid-19 (SARS-CoV-2) pandemic: A review, Chaos, Solitons and Fractals. 139 (2020) 110059. https://doi.org/10.1016/j.chaos.2020.110059.
[2] T. Davenport, R. Kalakota, The potential for artificial intelligence in healthcare, Future Healthcare Journal. 6 (2019) 94–98.
[3] G. Pinter, I. Felde, A. Mosavi, P. Ghamisi, R. Gloaguen, COVID-19 Pandemic Prediction for Hungary; A Hybrid Machine Learning Approach, SSRN Electronic Journal. (2020). https://doi.org/10.2139/ssrn.3590821.
[4] A.S.R. Srinivasa Rao, J.A. Vazquez, Identification of COVID-19 can be quicker through artificial intelligence framework using a mobile phone-based survey when cities and towns are under quarantine, Infection Control and Hospital Epidemiology. 41 (2020) 826–830. https://doi.org/10.1017/ice.2020.61.
[5] S. Kushwaha, S. Bahl, A.K. Bagha, K.S. Parmar, M. Javaid, A. Haleem, R.P. Singh, Significant applications of machine learning for covid-19 pandemic, Journal of Industrial Integration and Management. 5 (2020) 453–479.
[6] R. Ali, S. Lee, T.C. Chung, Accurate multi-criteria decision making methodology for recommending machine learning algorithm, Expert Systems with Applications. 71 (2017) 257–278. https://doi.org/10.1016/j.eswa.2016.11.034.
[7] I.P.A. Costa, S.M.D.N. Maêda, L.F.H.S.B. Teixeira, C.F.S. Gomes, M.D. Santos, Choosing a hospital assistance ship to fight the covid-19 pandemic, Revista de Saude Publica. 54 (2020) 79. https://doi.org/10.11606/s1518-8787.2020054002792.
[8] M.Â.L. Moreira, C.F.S. Gomes, M. dos Santos, M. do Carmo Silva, J.V.G.A. Araujo, PROMETHEE-SAPEVO-M1 a Hybrid Modeling Proposal: Multicriteria Evaluation of Drones for Use in Naval Warfare, in: Springer Proceedings in Mathematics & Statistics, 1st ed., Springer, Cham, 2020: pp. 381–393. https://doi.org/10.1007/978-3-030-56920-4_31.
[9] C.F.S. Gomes, M. dos Santos, L.F.H. de S. de B. Teixeira, A.M. Sanseverino, M. Barcelos, SAPEVO-M a group multicriteria ordinal ranking method, Pesquisa Operacional. 40 (2020) 1–20. https://doi.org/10.1590/0101-7438.2020.040.00226524
[10] J.-P. Brans, Y. De Smet, PROMETHEE methods, in: Multiple Criteria Decision Analysis: State of the Art Surveys, (2016).
[11] A. Ishizaka, G. Resce, B. Mareschal, Visual management of performance with PROMETHEE productivity analysis, Soft Computing. 22 (2018) 7325–7338. https://doi.org/10.1007/s00500-017-2884-0.
[12] N.A.V. Doan, Y. De Smet, An alternative weight sensitivity analysis for PROMETHEE II rankings, Omega (United Kingdom). 80 (2018) 166–174. https://doi.org/10.1016/j.omega.2017.08.017.
[13] J.P. Brans, P. Vincke, B. Mareschal, How to select and how to rank projects: The Promethee method, European Journal of Operational Research. 24 (1986) 228–238. https://doi.org/10.1016/0377-2217(86)90044-5.
[14] J.P. Brans, B. Mareschal, The PROMCALC & GAIA decision support system for multicriteria decision aid, Decision Support Systems. 12 (1994) 297–310. https://doi.org/10.1016/0167-9236(94)90048-5.
[15] M.Â. Moreira, I.P. de Araújo Costa, M.T. Pereira, M. dos Santos, C.F. Gomes, F.M. Muradas, PROMETHEE-SAPEVO-M1 a Hybrid Approach Based on Ordinal and Cardinal Inputs: Multi-Criteria Evaluation of Helicopters to Support Brazilian Navy Operations, Algorithms . 14 (2021). https://doi.org/10.3390/a14050140.
[16] A.O. de Oliveira, H.L.S. Oliveira, C.F.S. Gomes, P.C.C. Ribeiro, Quantitative analysis of RFID' publications from 2006 to 2016, International Journal of Information Management. 48 (2019) 185–192. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2019.02.001.
[17] G.R. Shinde, A.B. Kalamkar, P.N. Mahalle, N. Dey, J. Chaki, A.E. Hassanien, Forecasting Models for Coronavirus Disease (COVID-19): A Survey of the State-of-the-Art, SN Computer Science. 1 (2020) 1–15. https://doi.org/10.1007/s42979-020-00209-9.
[18] M. Kuhn, K. Johnson, Applied predictive modeling, 2013. https://doi.org/10.1007/978-1-4614-6849-3.
[19] S. Wang, B. Kang, J. Ma, X. Zeng, M. Xiao, J. Guo, M. Cai, J. Yang, Y. Li, X. Meng, B. Xu, A deep learning algorithm using CT images to screen for Corona Virus Disease (COVID-19), MedRxiv. (2020). https://doi.org/10.1101/2020.02.14.20023028.
[20] B. Mareschal, Visual PROMETHEE, (2011).