International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2022): 7.942

Benchmarking Machine Learning Methods COVID-19 Classification using MCDM technique

Suad M. Shakor[1]

[1]Computer Science Department, College of Computer Science and Mathematics, Tikrit University (TU), Tikrit, Iraq

Abstract: ***Different machine learning in the academic literature used to classify the COVID-19. The main question is which is the best method based on multi criteria evaluation. The benchmarking of COVID-19 machine learning methods, which is recognized as a multi-criteria decision making (MCDM) problem. In this paper we applied different machine learning methods on COIVD-19 to extract the decision matrix and applied TOPSIS to achieved the final rank and select the best machine learning. The result of this paper showing the Logistic Regression is the best method. Finally, this research presents many benefits, especially for hospitals and medical clinics with a view to speed up the diagnosis of patients suffering from COVID-19 using the best machine learning method.***

Keywords: COVID-19, Machine learning, Multi-criteria decision making, MCDM

1. Introduction

The diagnosis based on radiological images is a fast process and also has some advantages over the PCR test in terms of the recognition accuracy in the earlier phases of the COVID-19, the system's backbone is the need for experts to understand the images. Basically, diagnostic strategies based on Artificial Intelligence (AI) will allow experts to obtain a precise and a straightforward description of the X-ray images to identifying the COVID-19 [1-3]. The provision of healthcare includes the advancement of emerging technologies such as AI, Machine Learning (ML), Big Data, and Internet of Things (IoT), to tackle new diseases[4]. With a view to monitor the disease, AI can be utilized in tracking the spread of COVID-19 based on location and time. It has been marked by Persisting observations that COVID-19 has respiratory behaviors which differ from normal cold and seasonal influenza, showing extreme tachypnea (fast breathing) [5]. Machine and deep learning have become established and prestigious disciplines in deploying artificial intelligence to mine, analyze, identify and recognize patterns from data. Increasing the size of clinical data, varying data sources and the advances of those fields have enabled to get the benefit of clinical decision making and computer-aided systems which is increasingly becoming vital [6]. Besides, as the growth rate of COVID-19 is non-stationary and non-linear, maintaining the excellence in healthcare process and accurately predict COVID-19, play a significant role. Recently, various machine learning models have been used for COVID-19 prediction such as ANN [7], K-Nearest Neighbor (KNN) classifier [8], Support Vector Machines (SVM), Naive Bayes (NB), Logistic Regression (LR), Linear Discriminant Analysis (LDA), Random Forest (RF) and Decision Trees (DT) [9]. On the other hand, two common criteria are used in the literature to evaluate ML algorithms which applied for COVID-19 diagnosis including (i) group reliability and (ii) time complexity. Furthermore, several sub-criteria belonging to the reliability group have been considered including but are not limited to f1-score, precision, average accuracy, error rate, recall, true negative (TN), true positive (TP), false negative (FN), and false positive (FP) [10] and AUC [11]. However, for evaluating and benchmarking the ML methods considering all the aforementioned criteria simultaneously led us to the multi criteria problem [10]. The multi criteria problem can found with the criteria have trade-off (i.e. between the accuracy and time criteria) [12, 13]. And the conflict criteria is another issue when making the evaluation process [14, 15]. Therefore, multi criteria decision making is the best scheme that can be used to evaluating and benchmarking the ML methods over multi criteria evaluation[15]. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is one of the most technique used to solve MCDM problem [10, 12, 16, 17]. In this paper we applied TOPSIS to achieved the final rank and select the best machine learning.

2. Methodology

In this section the proposed framework of evaluation and benchmarking the machine learning methods for classifying COVID-19 based on the TOPSIS is presents in details.

Phase 1: Creating the COVID-19 Machine Learning Methods Decision Matrix.

The decision matrix of this research contains two main parts. The first part related to alternatives (the machine learning methods) and the second part related to the evaluation criteria.

The alternatives are the different elements that are targeted to be ranked based on decision-makers, expert opinion, and MCDM techniques. In this study, eight different ML algorithms, linear and nonlinear, were frequently applied to diagnose COVID-19. Therefore, as alternatives in the DM, we consider K-Nearest Neighbors (K_NN), Gradient Boosting (GB), Support Vector Machines (SVM), Decision Tree (DT), Logistic Regression (LR), Artificial Neural Network (ANN), Random Forest (RF), and Naive Bayes (NB) as our selected machine learning models. The evaluation criteria refer to the various measurements from which the alternatives could be evaluated and benchmarking we utilized the criteria: classification accuracy (CA), F1 score, recall, precision, log loss, specificity, and Area Under the Curve (AUC) which are the most prevalent measures [18, 19]. There are four important confusion matrix parameters used with the mathematical formulation for recall, precision, accuracy, and F1 score. In addition to four expressions which are True Positive (TP) referring to the number of accurately detected positive samples, True Negative (TN) referring to the negative samples which are correctly detected, False positive (FP) referring to the number of negative samples assorted as positive, and last but not least, the number of positive specimens predicted as unfavourable referred as False Negative (FN). Finally, in Table 1 present the decision matrix.

Table 1: The decision matrix

Alternatives	Train time [s]	Test time [s]	AUC	CA	F1	Precision	Recall	LogLoss	Specificity
Neural Network	170.281	2.859	0.996348842	0.970532319	0.970536119	0.970634585	0.970532319	0.120653235	0.983664273
SVM	53.793	4.024	0.996283375	0.967680608	0.967633013	0.967913827	0.967680608	0.09635078	0.981727867
Logistic Regression	7.353	1.59	0.994346638	0.958174905	0.958217865	0.958408258	0.958174905	0.233274449	0.976842133
kNN	4.412	5.274	0.98892582	0.937262357	0.937270789	0.938977386	0.937262357	0.339680905	0.964713178
Random Forest	18.635	1.546	0.990371553	0.933460076	0.93361603	0.933882482	0.933460076	0.227589409	0.964689334
Naive Bayes	5.554	1.504	0.966154159	0.900190114	0.900165988	0.900320941	0.900190114	3.150001339	0.947118754
Tree	15.561	0.021	0.916583241	0.891634981	0.891641318	0.891688177	0.891634981	2.123195663	0.943975329
AdaBoost	11.153	1.347	0.901379175	0.868821293	0.869036521	0.869435613	0.868821293	4.530752037	0.933064247

Phase 2: TOPSIS to Benchmarking ML Methods

In this section we present the steps and the equations of TOPSIS:

Step 1: Construct the normalized decision matrix: This process tries to transform the various attribute dimensions into non-dimensional attributes, which allows comparison across the attributes.

One way is to take the outcome of each criterion divided by the norm of the total outcome vector of the criterion at hand. An element r_{ij} of the normalized decision matrix R can be calculated as;

$$r_{ij} = \boldsymbol{x_{ij}} \Big/ \sqrt{\sum_{i=1}^{m} \boldsymbol{x_{ij}^2}} \qquad (\mathbf{1})$$

Consequently, each attribute has the same unit length of vector.

Step 2: Construct the weighted, normalized decision matrix

In this process, a set of weights $w = w_1, w_2, w_3, \cdots, w_j, \cdots, w_n$, $\sum_{j=1}^{m} w_j = 1$ from the decision maker is accommodated to the normalized decision matrix; the resulted matrix can be calculated by multiplying each column from normalized decision matrix (R) with its associated weight w_j. Therefore, the weighted normalized decision matrix V is equal to

This process produces the new matrix V where V is expressed as

$$V = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \cdots & w_n r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ w_1 r_{m1} & w_2 r_{m2} & \cdots & w_n r_{mn} \end{bmatrix}$$

Step 3: Determining the ideal and negative ideal solutions

In this process, two artificial alternatives A* (the ideal alternative) and, A⁻ (the negative ideal alternative) are defined as:

$$A^* = \left\{ \left(\left(\max_i v_{ij} \middle| j \in J \right), \left(\min_i v_{ij} \middle| j \in J^- \right) \middle| i = 1,2,\ldots,m \right) \right\} = \{v_1^*, v_2^*, \ldots, v_j^*, \cdots v_n^*\} \qquad (\mathbf{2})$$

$$A^- = \left\{ \left(\left(\min_i v_{ij} \middle| j \in J \right), \left(\max_i v_{ij} \middle| j \in J^- \right) \middle| i = 1,2,\ldots,m \right) \right\} = \{v_1^-, v_2^-, \ldots, v_j^-, \cdots v_n^-\} \qquad (3)$$

Where, J = {j = 1,2, … , n|j associated with benefit criteria}
J^{-}= {j = 1,2, … , n|j associated with benefit criteria}

Then it is certain that the two created alternatives A* and A- indicate the most preferable alternative (ideal solution) and the least preferable alternative (negative-ideal solution) respectively.

Step 4: calculate separation measurement based on the Euclidean distance

The separation between each alternative can be measured by the n-dimensional Euclidean distance. The separation of each alternative from the ideal one is then given by

$$S_{i^*} = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^*\right)^2}, \quad i = (1,2,\cdots m) \qquad (4)$$

Similarly, the separation from the negative-ideal one is given by

$$S_{i^-} = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2}, \quad i = (1,2,\cdots m) \qquad (5)$$

Step 5: Calculate closeness to the ideal solution calculation

In the process, the closeness of A_i to the ideal solution A^* is defined as:

$$C_{i^*} = S_{i^-}/(S_{i^*} + S_{i^-}), \quad 0 < C_{i^*} < 1, \quad i = (1,2,\cdots m) \qquad (6)$$

It is clear that $C_{i^*} = 1$ if and only if $(A_i = A^*)$, similarly, $C_{i^*} = 0$ if and only if $(A_i = A^-)$ An alternative A_i is closer to A* as Ci * approaches to 1.

Step 6: Rank the preference order: A set of alternatives can now be preference ranked according to the descending order of C*.

3. Result and discussion

In this section we present the result of TOPSIS was applied on the decision matrix. the final result and the final rank is reported in Table 2.

Alternatives	Score	Rank
Neural Network	0.450773	8
SVM	0.633592	5
Logistic Regression	0.860462	1
kNN	0.63258	6
Random Forest	0.849902	2
Naive Bayes	0.657177	4
Tree	0.766449	3
AdaBoost	0.56747	7

According to Table 2, the best alternative with the highest score is Logistic Regression (i.e. 0.860462). on the other hand, the worst alternative with lowest score is Neural Network (i.e. 0.450773). These result showing that Logistic Regression is the best method can use to classify the COVID-19 depend on the data set was used in this paper. We can make a recommendation to the hospitals and medical clinics to use Logistic Regression machine learning method.

4. Conclusion

This research achieved the evaluation and benchmarking of the COVID-19 machine learning methods using Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The methodology of this research divided into two main parts. The first part related to extracting the decision matrix. And the second part related to TOPSIS method was used to achieve the final rank for the machine learning methods. The result showed the Logistic Regression is the best machine learning method. Finally, this research presents many benefits, especially for hospitals and medical clinics, in order to speed up the diagnosis of patients suffering from a COVID-19 by utilizing the best machine learning method.

5. References

[1] Ucar, F. and D. Korkmaz, *COVIDiagnosis-Net: Deep Bayes-SqueezeNet based Diagnostic of the Coronavirus Disease 2019 (COVID-19) from X-Ray Images.* Medical Hypotheses, 2020: p. 109761.
[2] Ahmed, M., et al. *Automatic COVID-19 pneumonia diagnosis from x-ray lung image: A Deep Feature and Machine Learning Solution*. in *Journal of Physics: Conference Series*. 2021. IOP Publishing.
[3] Garfan, S., et al., *Telehealth utilization during the Covid-19 pandemic: A systematic review.* Computers in biology and medicine, 2021: p. 104878.
[4] Vaishya, R., et al., *Artificial Intelligence (AI) applications for COVID-19 pandemic.* Diabetes & Metabolic Syndrome: Clinical Research & Reviews, 2020.
[5] Kumar, A., P.K. Gupta, and A. Srivastava, *A review of modern technologies for tackling COVID-19 pandemic.* Diabetes & Metabolic Syndrome: Clinical Research & Reviews, 2020.
[6] Apostolopoulos, I.D. and T.A. Mpesiana, *Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks.* Physical and Engineering Sciences in Medicine, 2020: p. 1.
[7] Hasan, N., *A Methodological Approach for Predicting COVID-19 Epidemic Using EEMD-ANN Hybrid Model.* Internet of Things, 2020: p. 100228.
[8] Shaban, W.M., et al., *A new COVID-19 Patients Detection Strategy (CPDS) based on hybrid feature selection and enhanced KNN classifier.* Knowledge-Based Systems, 2020. **205**: p. 106270.
[9] Mohamadou, Y., A. Halidou, and P.T. Kapen, *A review of mathematical modeling, artificial intelligence and datasets used in the study, prediction*

and management of COVID-19. Applied Intelligence, 2020. **50**(11): p. 3913-3925.

[10] Mohammed, M.A., et al., *Benchmarking Methodology for Selection of Optimal COVID-19 Diagnostic Model Based on Entropy and TOPSIS Methods.* IEEE Access, 2020.

[11] Alakus, T.B. and I. Turkoglu, *Comparison of deep learning approaches to predict covid-19 infection.* Chaos, Solitons & Fractals, 2020. **140**: p. 110120.

[12] Zughoul, O., et al., *Novel triplex procedure for ranking the ability of software engineering students based on two levels of AHP and group TOPSIS techniques.* International Journal of Information Technology and Decision Making, 2021.

[13] Alsalem, M., et al., *Multiclass benchmarking framework for automated acute Leukaemia detection and classification based on BWM and group-VIKOR.* Journal of medical systems, 2019. **43**(7): p. 212.

[14] Abd Ghani, M.K., et al., *Decision-level fusion scheme for nasopharyngeal carcinoma identification using machine learning techniques.* Neural Computing and Applications, 2020. **32**(3): p. 625-638.

[15] Malik, R., et al., *Novel Roadside Unit Positioning Framework in the Context of the Vehicle-to-Infrastructure Communication System Based on AHP—Entropy for Weighting and Borda—VIKOR for Uniform Ranking.* International Journal of Information Technology & Decision Making, 2021: p. 1-34.

[16] Alaa, M., et al., *Assessment and ranking framework for the English skills of pre-service teachers based on fuzzy Delphi and TOPSIS methods.* IEEE Access, 2019. **7**: p. 126201-126223.

[17] Salih, M.M., B. Zaidan, and A. Zaidan, *Fuzzy decision by opinion score method.* Applied Soft Computing, 2020: p. 106595.

[18] Xie, Y., et al. *Beyond classification: Structured regression for robust cell detection using convolutional neural network*. in *International conference on medical image computing and computer-assisted intervention*. 2015. Springer.

[19] Sukumar, P. and R. Gnanamurthy, *Computer aided detection of cervical cancer using pap smear images based on adaptive neuro fuzzy inference system classifier.* Journal of Medical Imaging and Health Informatics, 2016. **6**(2): p. 312-319.