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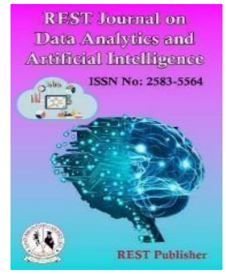

Comparative Analysis of Machine Learning Algorithms A MOORA-Based Methodology

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Abstract: *This research explores the application as machine learning continues to grow in significance across diverse fields such as healthcare, finance, image processing, and decision support systems, its real-world application still faces challenges despite its mathematical sophistication. The study focuses on five algorithms assessing their performance using four key indicators: YES, classification accuracy, percentage of correct classifications, number of attributes, and number of data instances processed. The MOORA method, known for its reliability in multi-criteria decision-making, was employed to normalize the data, assign equal weights to each criterion, and construct a weighted normalized decision matrix. This approach enabled an impartial ranking of the algorithms based on their collective performance across all criteria. According to the results, neural networks received the highest evaluation score (0.1371), placing them first, followed by random forest (0.1316) and decision tree (0.1000). Naïve Bayes and decision table ranked fourth and fifth, respectively, with negative scores. The study demonstrates that the MOORA method offers a solid and objective framework for evaluating machine learning algorithms by considering multiple performance dimensions. This comprehensive evaluation assists decision-makers in understanding the relative strengths and weaknesses of each algorithm, supporting more informed choices for specific applications. Ultimately, this research contributes to the advancement of algorithm assessment methodologies and emphasizes the value of multi-objective optimization in the comparative analysis of computational intelligence systems.*

Keywords*: Algorithm Performance Evaluation, Multi-Objective Optimization, Decision Tree Classification, Normalized Decision Matrix, Computational Intelligence*

1. INTRODUCTION

Machine learning algorithms are categorized as classifiers depending on the intended outcome. Supervised learning, for instance, develops a function that links input data to expected outputs. [1] Machine learning algorithms are extensively applied in areas such as image recognition, big data analytics, speech processing, medical diagnosis, statistical modelling, pattern recognition, classification, and forecasting. [2] Machine learning enables systems to learn and improve without explicit programming. By constructing models using these algorithms, it's possible to support early disease diagnosis and suggest potential treatments. Early detection and timely intervention are key strategies for lowering mortality rates associated with various illnesses. [3] Machine learning enables computers to learn autonomously and improve through experience without the need for explicit programming. It proves especially valuable in situations where crafting high-performance, rule-based algorithms is impractical.[4] While machine learning algorithms are grounded in complex mathematics and theory, understanding the underlying principles isn't essential for effectively applying them to achieve meaningful outcomes. From a practical standpoint, machine learning is accessible, and a dedicated developer can quickly begin making impactful contributions. This book aims to guide you toward that goal. [5] Challenges in machine learning often arise from imbalanced sampling, where rare events encountered during testing are absent in the training phase, leading to misclassification. To address such issues, statistician Leo Bremen from the University of California, Berkeley, introduced an algorithm that enhances classification performance using random sampling and feature selection. [6] Machine learning (ML) techniques are not a universal solution to all challenges posed by environmental data in advertising, but they offer a valuable set of tools that merit careful consideration for addressing specific related issues. Fundamentally, many ML problems stem from traditional, well-established statistical concepts. [7] We examined the ongoing significance of these challenges within the field of machine learning, provided an overview of the validation methods employed in the reviewed studies in the Validation Strategies section, and elaborated on the associated techniques in the Analysis Methods section. [8] Machine learning (ML), a branch of artificial intelligence (AI), allows computers to learn from experience and improve their performance without being explicitly programmed.[9] It involves developing systems that can interpret and manage complex, unfamiliar data. ML techniques are generally divided into three primary types: supervised learning, unsupervised learning, and reinforcement learning. [10]Both machine learning and deep learning play a crucial role in enabling systems to perform expert-level tasks, aiding in prediction and informed decision-making. [11]This technology has widespread applications across various sectors, including finance, bioinformatics, business, computer vision, and education. [12] Data mining, in particular, relies heavily on machine learning algorithms to uncover meaningful insights from large datasets. A common challenge is determining which algorithm is best suited for a specific dataset. [13]Most machine learning models require parameter settings—such as learning rates or model complexity—that can complicate implementation, prompting interest in algorithms with fewer dependencies.[14] Some tools incorporate pre-processing techniques along with evolutionary approaches like the Pittsburgh and Michigan models, offering engineers a more comprehensive and transparent analysis of learning models. This section also reviews related studies using the KDD dataset, highlighting its value in developing, evaluating, and benchmarking various machine learning algorithms. [15]

2. MATERIAL AND METHOD

Decision Table: A decision table is a systematic way to represent and analyze complex decision logic. It organizes conditions and their corresponding actions in a tabular format, simplifying the interpretation and management of various input-output scenarios.
Random Forest: Random Forest is a powerful machine learning method that utilizes an ensemble of decision trees to generate predictions. By constructing each tree from randomly selected data samples and features, it enhances prediction accuracy and minimizes the risk of over fitting.
Naive Bayes: Naive Bayes is a probabilistic classification method grounded in Bayes' theorem. It operates under the assumption that input features are independent, which simplifies computation. Despite this unrealistic assumption, it performs effectively in areas like email spam detection and text classification.
Neural Networks: Neural networks are advanced computational frameworks modelled after the human brain's neural structure. Consisting of layers of connected processing units (neurons), they excel at identifying complex patterns and are widely used in applications such as image analysis and automated decision-making.
Decision Tree: A decision tree is a visual and analytical tool that structures decision-making in a tree-like diagram. It breaks down problems into branches of choices, each leading to different outcomes, thus simplifying complex decisions into smaller, manageable steps.
Accuracy of YES: In statistics, "accuracy" refers to the consistency of repeated measurements, not necessarily their closeness to the actual value. A process can be considered accurate if it produces the same result consistently, even if that result is not perfectly correct.
Correctly Classified (%): This metric indicates the percentage of instances a model correctly predicts or classifies, reflecting the effectiveness of the algorithm in classification tasks. It measures how often the model's predictions align with the true labels.
Attributes: Attributes describe specific characteristics or properties of an object, entity, or data point. In computing, they define the qualities or behaviours of classes and objects, playing a key role in how systems and data structures function.
Number of Instances: This refers to the total count of specific entities—such as data samples, objects, or program executions—within a system. In programming or data analysis, an instance typically represents a unique occurrence of a class, object, or data entry.

MOORA Method: The MOORA method is a decision-making approach used to evaluate and rank alternatives based on multiple criteria. It involves normalizing the data and calculating a ratio to compare each option across various objectives. By balancing both beneficial and non-beneficial criteria, the method provides a clear and systematic framework for identifying the most favourable choice among several alternatives. [16]This aligns with the economic principle of diminishing marginal utility, which supports balanced, neutral solutions. In this study, the MOORA method is applied to address common material selection challenges. [17]MOORA, which relies on ratio analysis and dimensionless values, enables contractor rankings without subjective bias. One practical example involved ranking major residential maintenance contractors in Vilnius, Lithuania. [18] Overall, MOORA demonstrates clear superiority over other multi-objective optimization techniques, with both components yielding consistent rankings in Lithuania's facilities sector, thereby reinforcing the method's robustness. [19] By applying the valuation results obtained through the MOORA method, it is possible to estimate the market value of individual apartments or condominiums in Lithuania and other countries. [20] Involves the simultaneous optimization of multiple, often conflicting objectives within defined constraints. The MOORA method, originally developed for this purpose, has proven effective in addressing complex decision-making challenges, particularly in manufacturing contexts. [21] In response to such challenges, a utilizing the MOORA method has been designed to aid in evaluating teacher performance. [22] This approach has also been applied to identify optimal bank branch locations by evaluating key demographic, economic, and investment factors. Both the AHP and MOORA methods have been utilized in cross-country studies to determine the most suitable branch locations.[23] MOORA, one of the more recent methods in the field of employs a process and is characterized by straightforward operational steps that aggregate various decision criteria. [24] MOORA method in decision support systems for evaluating scholarship eligibility, offering valuable insights into its practical application.[25] One such study specifically analyzed the strengths and limitations of MOORA in the context of scholarship admissions. However, like many traditional MCDM methods, MOORA relies on discrete numerical values, which may limit its effectiveness in accurately representing many real-world problems that require more nuanced or continuous data. [26] Based on the above explanation, the MOORA method can be used to identify the best employees for a company. By applying this method, managers or decision-makers can objectively select the most suitable employee(s) according to the company's needs this approach helps prevent biased or unprofessional decisions, such as those influenced by bribery, personal relationships, or favouritism. [27]The weighting process, which is typically manual, can be automated using ROC, resulting in a more accurate and optimal weighting outcome. The difference between the SAW and MOORA methods in this context lies in how the characteristics are weighted, with ROC improving the accuracy in the current study compared to previous ones. The primary aim of this research is to compare the SAW and MOORA methods to determine the best approach for evaluating the performance of teaching assistants. [28] Additionally, the study evaluates the MOORA multi-criteria decision-making technique to decide the optimal location for establishing a logistics centre in the Black Sea region. The research is structured into several sections: an introduction to the Black Sea region, an overview of the MOORA technique, a case study, and a final conclusion.[29] Furthermore, the developed system allows Yayasan alumni to complete all screening processes in one place, streamlining the examination procedure. MOORA is a versatile system that simultaneously optimizes both beneficial criteria and those that represent costs or lack value. [30]

3. ANALYSIS AND DISCUSSION

TABLE 1. Machine learning algorithm

	Accuracy of YES	Correctly Classified (%)	Attributes	No of instances
Decision Table	12.35	156.34	78.45	76.37
Random Forest	64.34	126.00	25.56	22.34
Naive Bays	24.34	129.90	29.18	35.34
Neural Networks	54.23	139.34	12.23	27.56
Decision Tree	44.44	177.45	36.45	19.34

Table 1 presents a comparison of machine learning algorithms based on the MOORA method. Random Forest achieves the highest accuracy (64.34%) but handles the fewest instances (22.34). Decision Tree records the highest rate of correct classifications (177.45%). Neural Networks offer a balanced performance with 54.23% accuracy. Decision Table performs the weakest, while Naïve Bayes demonstrates moderate results across various attributes.

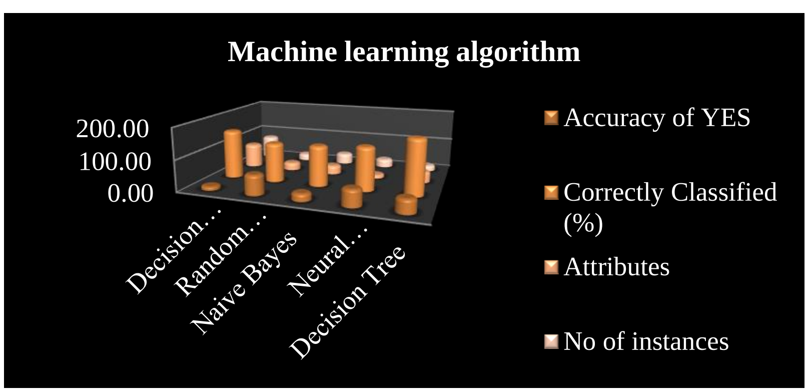

FIGURE 1. Machine learning algorithm

Figure 1 displays the performance assessment of different machine learning algorithms using the MOORA method. Method. Random Forest achieves the highest accuracy (64.34%) but processes the fewest instances (22.34). Decision Tree ranks highest in correct classifications (177.45%). Neural Networks demonstrate balanced accuracy (54.23%), whereas Decision Table performs the weakest. Naïve Bayes shows average effectiveness.

TABLE 2. Normalized Data

Accuracy of YES	Correctly Classified (%)	Attributes	No of instances
0.1248	0.4755	0.8207	0.8181
0.6499	0.3832	0.2674	0.2393
0.2459	0.3951	0.3053	0.3786
0.5478	0.4238	0.1279	0.2952
0.4489	0.5397	0.3813	0.2072

Table 2 displays normalized values derived using the MOORA method, reflecting standardized performance across key indicators. The highest normalized accuracy (0.6499) aligns with the lowest instance value (0.2393), suggesting a trade-off. Variations are evident across attributes and classification rates, with the first row showing the highest attribute and instance normalization (0.8207 and 0.8181).

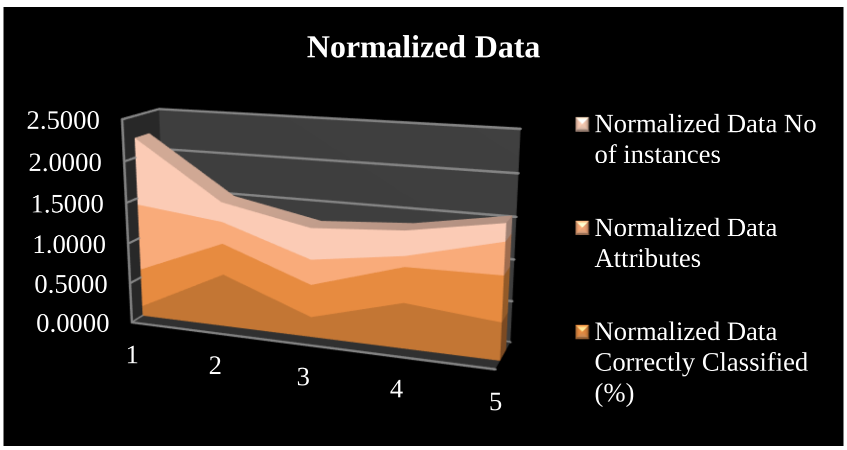

FIGURE 2. normalized data

Figure 2 presents data normalized through the MOORA method, emphasizing standardized values across essential metrics. The highest normalized accuracy (0.6499) is associated with the lowest number of instances (0.2393), suggesting an inverse correlation. The first entry demonstrates high normalization in both attributes (0.8207) and instances (0.8181), while other records show diverse performance levels.

TABLE 3. Weight

Weight			
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25

Table 3 presents the weights applied through the MOORA method, assigning equal significance to each criterion. Every attribute—accuracy, correct classification, attribute count, and number of instances—is uniformly weighted at 0.25. This even allocation promotes a fair evaluation, ensuring that all factors contribute equally to the decision-making process.

TABLE 4. Weighted Normalized decision matrix

Decision Table	0.0312	0.1189	0.2052	0.2045
Random Forest	0.1625	0.0958	0.0668	0.0598
Naive Bays	0.0615	0.0988	0.0763	0.0946

Neural Networks	0.1369	0.1060	0.0320	0.0738
Decision Tree	0.1122	0.1349	0.0953	0.0518

Table 4 illustrates the based on the MOORA method. It displays the performance of each algorithm across various metrics after equal weight distribution. Random Forest outperforms in the first metric (0.1625), while the decision matrix highlights strong performance in several areas. Naive Bayes shows average results, with Neural Networks and Decision Trees providing consistent performance across the metrics.

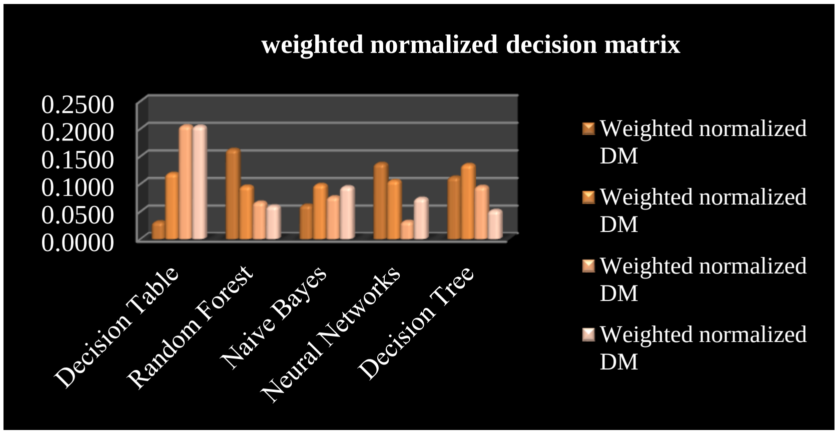

FIGURE 3. Weighted normalized decision matrix

Figure 3 presents the decision matrix based on the MOORA method, showcasing the performance of different algorithms across various metrics. Random Forest excels in the first metric (0.1625), while the Decision Table performs well across multiple metrics. Naive Bays demonstrates moderate performance, and Neural Networks and Decision Trees offer consistent results.

Table 5. MOORA result and rank

	Assessment value	Rank
Decision Table	-0.2596	5
Random Forest	0.1316	2
Naive Bays	-0.0107	4
Neural Networks	0.1371	1
Decision Tree	0.1000	3

Table 5 displays the MOORA analysis and results, indicating the evaluation values and rankings for each algorithm. Neural Networks lead with the highest evaluation value (0.1371), followed by Random Forest (0.1316). Decision Tree ranks third (0.1000), while Naive Bays and Decision Table are ranked fourth and fifth, with negative evaluation values.

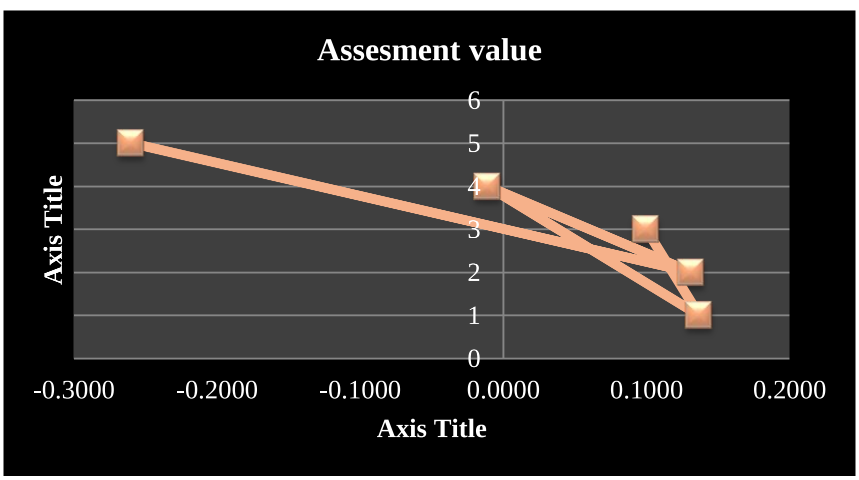

FIGURE 4. Assessment value

Figure 4 presents the MOORA analysis and results, displaying the evaluation values and rankings for each algorithm. Neural Networks top the rankings with the highest evaluation value (0.1371), followed by Random Forest (0.1316). Decision Tree ranks third (0.1000), while Naive Bays and Decision Table are ranked fourth and fifth, respectively, with negative values.

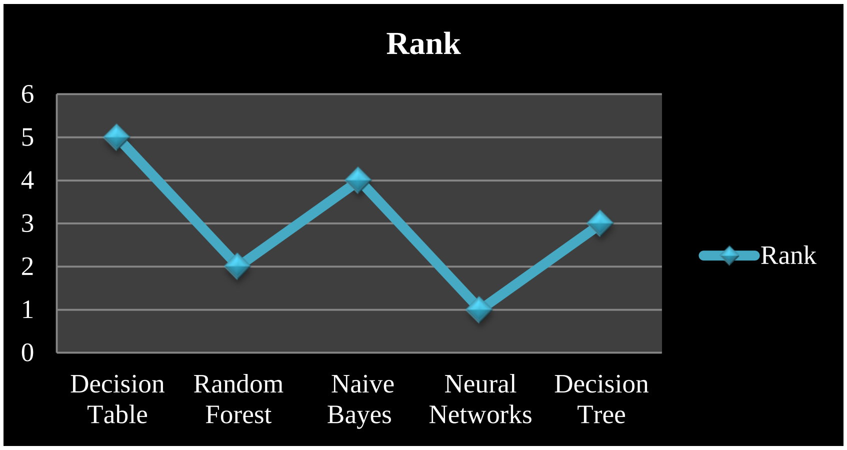

FIGURE 5. Rank

Figure 5 shows the rankings derived from the MOORA method. Neural networks rank first with the highest score of 0.1371, followed by Random Forest in second place with 0.1316. Decision Tree takes third place with a score of 0.1000, while Naive Bays and Decision Table are ranked fourth and fifth, with values of -0.0107 and -0.2596, respectively.

4. CONCLUSION

This study effectively demonstrated for the evaluation and ranking of machine learning algorithms. By assessing five commonly used algorithms—decision table, random four key performance metrics, we developed a structured and balanced framework for multi-criteria comparison that moves beyond conventional single-metric analysis. The results revealed that neural networks outperformed the other algorithms, attaining the highest evaluation score (0.1371) and ranking first overall due to their consistent performance across all metrics. Random forest followed with a score of 0.1316, while decision tree secured third place (0.1000). Naïve Bayes and decision table received negative scores, placing them fourth and fifth, respectively, which points to their relative inefficiency in a multi-criteria context. This research highlights the value of the MOORA method in addressing the complexity of algorithm selection by offering an objective, normalized and evenly weighted evaluation approach The findings emphasize the need to evaluate machine learning algorithms across multiple dimensions. Although random forest achieved the highest single-metric accuracy (64.34%), neural networks were ultimately ranked higher overall due to their more balanced results. This demonstrates how comprehensive multi-criteria analysis can yield different insights than single-metric evaluations. For researchers and practitioners; the study provides a clear, adaptable framework for algorithm selection that can be tailored to specific domains by adjusting performance metrics and weighting schemes.

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