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RESEARCH ARTICLE

Harnessing AI for Leadership Development: Predictive Model for Leadership Assessment

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ABSTRACT

The present paper has been devoted to the study conducted with the purpose of examining the possibility of applying Machine Learning techniques in classifying leadership based on structured survey data. The objective was to create a predictive model that would allow classifying leadership into three groups – Low, Medium, and High – based on behavior scores. The model was expected to offer a reliable tool for improving leadership development programs and recruitment processes by providing a precise and scalable leadership classification, The study illustrates the potential of advanced ML techniques for rethinking the traditional approaches to the assessment of leadership. Due to the use of advanced ensemble modeling, it was possible to ensure the high accuracy of 93.3% in leadership predicting. Such outcomes can generate considerable advantages for organizational development strategies. The use of ensemble machine learning in the domain of organizational behavior studies can be considered as a valuable academic contribution as it has demonstrated the capacity of determining the application of ensemble techniques for enhancing leadership studies. at the same time, it offers a useful instrument to develop more sophisticated and data-driven practices for leadership development.

Keywords: Machine learning, Leadership style classification, Ensemble learning, Predictive Analytics in HR, Quantitative leadership evaluation, AI in organizational development

1. Introduction

The development of advanced machine learning methods significantly impacted leadership assessment in organizational behavior. Leadership is one of the most critical concepts in examining organizational processes because of its impact on various organizational outcomes [1], such as employee engagement, team productivity, overall corporate prosperity, and even the presence of factors associated with routine organizational culture. Personality assessment is one of the most complicated challenges in psychology because of the subjective character of personality judgment. Nevertheless, leadership is one of the most researched and examined roles in psychology, and this fact allows for the application of various objectively validated questionnaires to assess leaders' behavior [2].

In the industrial and organizational psychology of the past decade, research in leadership assessment has been significantly developed. One of the latest trends in the field is machine learning, which categorizes latent constructs impacted by this or that aspect of leaders' behavior. In the present paper, the authors report on developing a powerful machine-learning tool capable of classifying leadership. For this purpose, the authors used a leadership questionnaire dataset containing information on various leadership indicators, such as transformational leadership or intellectual stimulation. The dataset was divided into three groups according to the level of behaviors, with two cut-off points, and the machine learning model was trained on these data.

The methodology is based on the use of several sophisticated machine learning models that have been investigated in several studies, including such types as Random Forest [3], Support Vector Machines [4], K-nearest neighbor [5] and Gradient Boosting [6]. These models favored the above specifics, with the high-dimensional ability and robust characteristics in classification challenges. Additionally, to refine and enhance the accuracy and viability of the prediction, the Stacking Ensemble approach was investigated and adopted [7] - [9]. As far as it is known, given each model's strengths and capacities, the Stacking Ensemble technique is based on combining them in favor of an individually better performance. Stacking uses a meta-model, Logistic Regression, in the present study to integrate and convert the predictions of each model into the final, optimal classification [10]. This benefits accuracy and reduces errors or poor performance of the final classification generalization.

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First, the specificity of this approach is reduced potential and opportunities for human bias. One of the most crucial drawbacks of human assessment is the heavy influence of those in favor and against a particular leader being objectively assessed. If the developed methodology heavily relies on purely quantitative data and objective algorithms, no room for such biased implementation can ruin the conceptual framework. In this way, the reliance on machine learning eliminates the potential for such a negative impact and does it in favor by reducing biasedness.

Secondly, methodology benefits from the machine learning characteristics in terms of being more scalable in leadership assessment. In this framework, more scalability indicates that, unlike the risks of losing quality in assessments of bigger populations, the machine models may easily operate and provide accurate leadership assessments for bigger datasets. This is not the case for human manual evaluation. Lastly, the overall predictive nature of the outcomes of these steps provides a way to predict future leadership success.

With the evolution of artificial intelligence, its adoption in leadership assessment is also likely to increase, and future research can potentially focus on utilizing even more advanced AI mechanisms, such as deep learning and neural networks [11]. The advancements of such AI mechanisms can make assessments even more accurate, reliable, and applicable in various contexts, eventually improving the effectiveness of leadership and the outcomes of organizations.

2. Literature Review

There are different algorithms and statistical methods used in leadership assessment, and depending on the nature of the assessment instrument and the desired outcomes, several algorithms and statistical methodologies are employed to evaluate leadership practices. Common algorithms and techniques for evaluating leaders include:

Factor analysis is a statistical technique for extracting underlying structures from data collection. Factor analysis is commonly used in leadership evaluation to isolate the most crucial features or behaviors [12]. Regression analysis establishes a connection between a set of independent variables and a set of predictor variables. Regression analysis may be used in leadership evaluation to determine which characteristics, skills, or context variables most indicate future performance as a leader [13]. Item Response Theory (IRT) estimates the latent skill or trait being tested; this statistical technique analyzes answers to multiple-choice questions. It is possible to gauge a leader's efficacy using IRT by analyzing their replies to a questionnaire [14]. Cluster analysis is a statistical technique for classifying data or cases into clusters with comparable features. Cluster analysis may be used in leadership evaluation to categorize candidates into teams based on shared leadership traits [15]. Content analysis is a technique used to dissect text or speech for underlying structures like themes or categories. Content analysis may be used to extract the most salient points from leadership narratives and interviews for use in evaluation [16].

Various artificial intelligence algorithms and techniques have been used in business management and leadership, such as natural language processing, NLP, decision trees, neural networks, support vector machines, and Bayesian Networks.

Researchers focus on how machine learning affects several aspects and recommend continuous investigation using the lenses of the digital era to approach leadership. Several studies have been conducted, such as automating leadership assessments [2] and understanding leadership traits in machine learning [17].

The NPL is a subset of AI that focuses on understanding and processing human language. To determine a leader's success, NLP may examine text data from various sources, including emails, social media, and performance reviews. In [18], NLP has been used to distinguish the employees' views regarding the organization's leaders. At the same time, in [19], the AI approaches address human resource management HRM and how it can enhance their work.

Another AI algorithm is the decision tree, a machine learning algorithm for classification and prediction. Decision trees may be used to forecast leadership performance and isolate the variables that most affect it in leadership assessments; Bekensiene and Hoskova [20] used them to identify the effective indicators of leadership. Then, in 2019, they implemented this model in Lithuania army forces, where their research helped to understand how troops might be categorized not just by military rank but also concerning how they respond to leadership indications [21].

In [22], the leadership styles have been addressed. How can they be predicted by using a localized multiple kernel learning method (LMKL)? Various NFs extracted from different modalities were utilized to detect leadership styles. However, the suggested technique was tested on two distinct types of data. To our knowledge, no in-the-wild dataset exists for leadership style prediction.

Inclusive leadership has been addressed using machine learning in [23]; their results show that the path of inclusive leadership's evolution is most clearly seen in its gradual transition from the field of education, where it primarily focuses on schools, students, diversity, and equity, to that of organizational behavior, where it primarily focuses on leaders, employee participation, the workplace, and situational factors. The current and future focus of inclusive leadership studies will be on the role of contextual variables.

Regarding automated assessments, research was conducted to assess and identify the leadership in college students [24]; this study presents LAIGA, a machine learning-based methodology for passively and automatically analyzing and selecting college student leaders based on their academic profiles and conduct in the LMS. (LMS). The proposed method deals with the issues of leadership evaluation and identification. The suggested technique is validated by a case study of graduating IT majors. It produced a MAPE of 5.87% in the leadership assessment task and an F1 of 83.2% in the leadership identification test. Consequently, the suggested strategy can predict leadership evaluation and identification post-graduation with as little information as available during the first year of college. Understanding the factors that contribute to the development of leadership skills and designing mechanisms that promote the growth of student leaders is made possible by the findings of this study. This study also sheds light on the ability to use machine learning technologies to assess and identify leadership in college students automatically. If grades and LMS activities can be obtained from students, the suggested technique may be easily applied to various academic disciplines.

3. Methodology

3.1. Dataset

To address the research questions, the study utilizes a dataset that combines behavioral assessments and structured surveys scored equally by several organizational leaders. Each instance in the dataset represents the evaluation of each respondent across multiple categories of leadership behavior. These categories are Core Transformational Leadership – modeling the way, encouraging the heart, challenging the process, inspiring a shared vision and ennobling the spirit. High-Performance Expectations – focusing on goals, setting high standards and not letting standards slip. Supportive Leader Behavior – understanding team members, acting supportive when required, and creating a friendly climate. Intellectual Stimulation – urging issues to be perceived from another angle, creating an environment to be imaginative and novel, and discussing things philosophically. The survey responses were provided on a Likert scale from 1 to 10, which allows for a quantitative analysis. The questionnaire used for collecting data is shown in Table 1.

Table 1. Questionnaire of Transformational Leadership

No.	Items
➢	***Core Transformational Leadership Behavior (CT)***
1	My leader defines the vision and mission of the organization clearly.
2	My leader sets a suitable role model.
3	My leader encourages the attainment of common goals.
➢	***High-Performance Expectation (HP)***
4	My leader encourages his subordinates to contribute to the organization.
5	My leader encourages his subordinates to perform at their best
6	My leader encourages his subordinates to achieve their best goals.
➢	***Supportive Leader Behavior (SL)***
7	My leader shows respect for his subordinates.
8	My leader shows concern for his subordinates.
9	My leader is concerned about the welfare of his subordinates.
10	My leader considers suggestions from subordinates before acting.
➢	***Intellectual Stimulation (IS)***
11	My leader encourages his subordinates to solve old problems in the right way.
12	My leader encourages subordinates to think about the best way to do the job.
13	My leader encourages his subordinates to use appropriate solutions to problems.

3.2. Data Preprocessing

1) Data Cleaning

The initial steps involved handling missing data and errors in data entry. Given the structured nature of survey data, missing values were imputed using the respective item's median score to maintain the data distribution's integrity.

2) Feature Engineering

Scores from related survey items were aggregated to create composite scores for each leadership dimension, enhancing the analytical robustness of the dataset.

3) Data Scaling

The features were standardized using the StandardScaler to ensure the model inputs had a mean zero and unit variance. This is particularly important for models sensitive to the scale of input features like SVM.

4) Categorization

The 'Total Transformational Leadership' score was calculated as the sum of all leadership dimension scores, and it was categorized into three groups (Low, Medium, and High) based on percentile thresholds to facilitate classification; the distribution is shown in Figure 1.

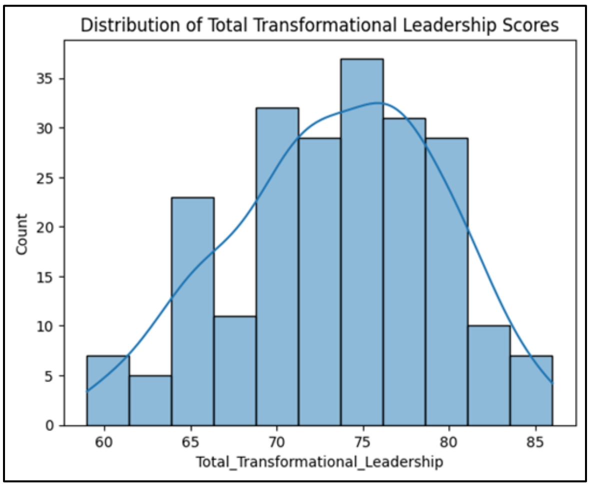

Figure 1. Distribution of Total Transformational Leadership Scores

3.3. Modelling Technique

1) Base Models

Random Forest is an ensemble learning method that constructs many decision trees at training time. It has high accuracy and robustness and works efficiently on large databases.

SVM is a powerful classifier that works well in high-dimensional spaces. It is useful when the number of dimensions surpasses the number of samples.

Gradient Boosting: It operates by constructing models in a phased sequence where each new model addresses the failures introduced by the already trained trees. It is widely used for its strong predictive power of any differential loss function.

2) Stacking Ensemble

A stacking approach was used, and the final estimator was a logistic regression model. Stacking allows combining the strengths of individual models to achieve better prediction accuracy and higher generalization to never-before-seen data. The selection of models was random. Random Forest, SVM, and Gradient Boosting were chosen because each had a particular strength that made them especially good at handling some complexity in data. Random Forest is not inclined to overfit and is good at dealing with non-linearity in data. SVM is effective in high-dimensional spaces, which is particularly important because leadership is multidimensional, and it is hard to compare the psychological traits of leadership by order of magnitude. Gradient Boosting is an excellent learner, and the need to minimize error sequentially is a good example of a problem where such a learner will be especially powerful. The diversity of these models, in the complementary nature of their strengths, is why they stick together.

Stacking allows the blending of these models efficiently to enhance the ensemble's overall well-performing capabilities. The final estimator was a logistic regression model because it provided clear probabilistic output. In addition, using logistic regression to stack predictions allows accounting for the logistic distribution of binary outcomes, which is the prettiest approach to dealing with a categorical response variable. This methodology allows for a sound framework for analyzing leadership more sophisticatedly using advanced data science tools and insights that can potentially revolutionize strategic human resource management.

3) Deep learning approach

To evaluate the effectiveness of deep learning in leadership classification, we implemented a Multi-Layer Perceptron (MLP) Neural Network. The model was designed with the following architecture:

- 4 hidden layers:
    - 128 neurons (first layer)

    - 64 neurons (second layer)
    - 32 neurons (third layer)
    - 16 neurons (fourth layer)
- Activation function: ReLU in all hidden layers
- Optimizer: Adam
- Loss function: Categorical Cross-Entropy
- Regularization: Alpha = 0.0001 to prevent overfitting
- Iterations: 1000 epochs for training stability

The dataset was normalized using MinMaxScaler to scale input features between 0 and 1. The target variable, representing leadership classification (Low, Medium, High), was one-hot encoded and categorized based on percentile thresholds. The dataset was split into 80% training and 20% testing sets. The model was trained using a batch size 16, optimizing through gradient descent-based Adam optimization.

4. Results

1) The ensemble machine learning model was validated using the data generated from the leadership behavior surveys. The classification effectively grouped the leadership styles as Low, Medium, and High depending on collecting the leadership dimensions' scores.

The Stacking Ensemble model, integrating predictions from Random Forest, SVM, and Gradient Boosting with a Logistic Regression meta-model, achieved the highest accuracy of 93.3%. This represents a significant improvement over the individual models, as the confusion matrix of each model is shown in Figures 2, 3, and 4, respectively.

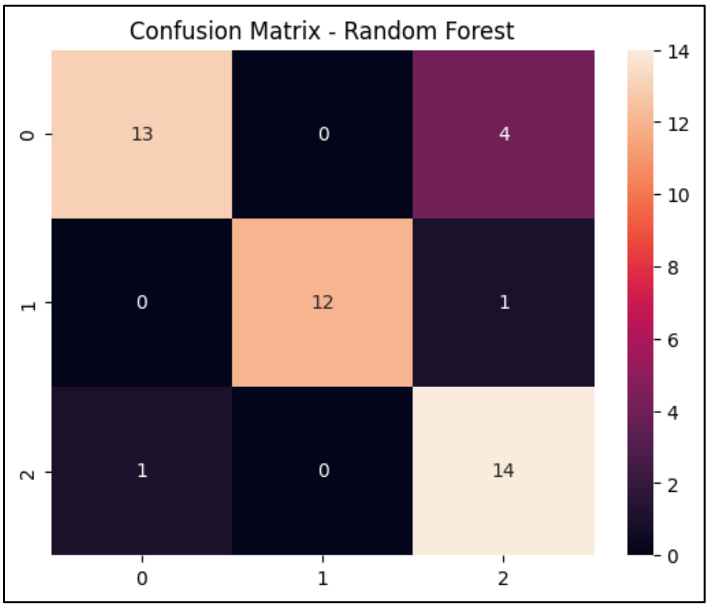

Figure 2. Random Forest Confusion Matrix

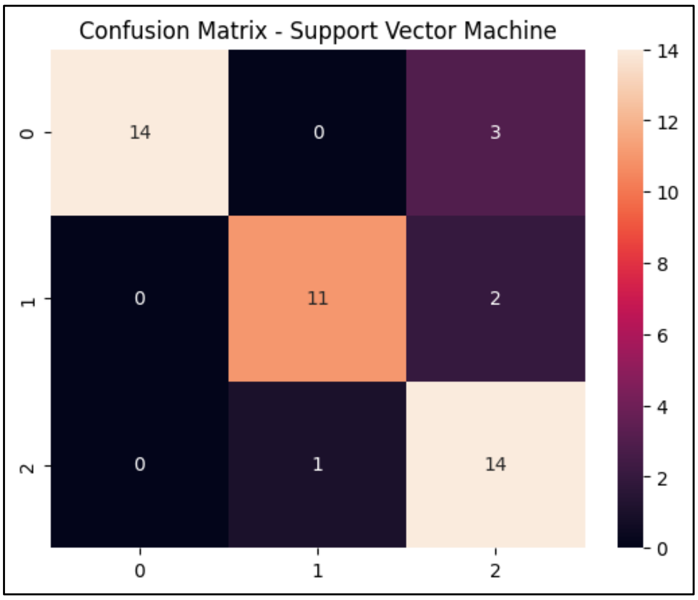

Figure 3. Support Vector Machine Confusion Matrix

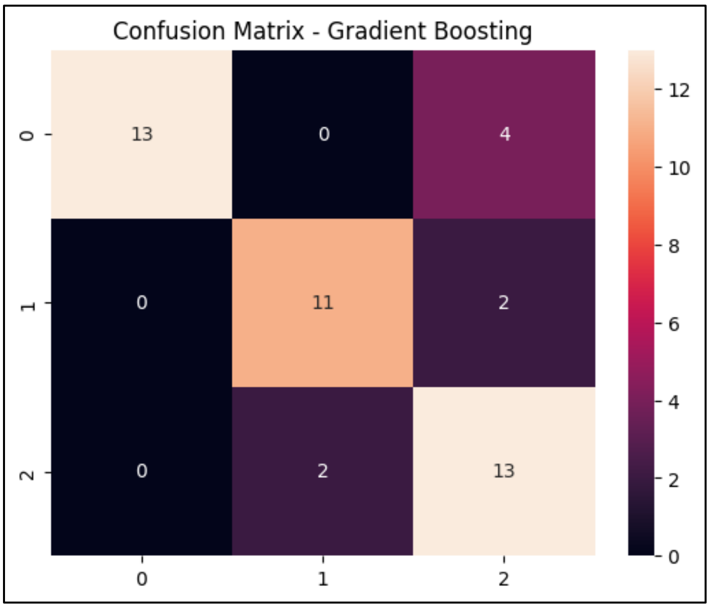

Figure 4. Gradient Boosting Confusion Matrix

The ensemble stacking model shows a better result, as shown in the confusion matrix of Figure 5.

These metrics indicate that the Stacking Ensemble model was particularly effective at identifying High and Medium leadership styles, with perfect precision in identifying Medium leadership styles. The 100% recall in High leadership style suggests that all instances of High leadership were correctly identified.

The superior performance of the Stacking Ensemble model can be attributed to its ability to harness the diverse strengths of the underlying base models, effectively mitigating their weaknesses. For instance, Random Forest provided a robust baseline with its decision tree-based approach, which is less prone to overfitting and good at handling the binary split of categorical data. At the same time, SVM contributed to the model's performance in high-dimensional spaces, which is crucial given the multi-dimensional nature of the data, and Gradient Boosting improved the model's ability to reduce bias and variance sequentially, addressing errors left by the previous models in the sequence.

The integration of these models through stacking, guided by a Logistic Regression meta-model, optimized the combination of their predictions. This likely led to improved accuracy and reliability in classifying leadership styles, as shown in the comparison histogram in Figure 6.

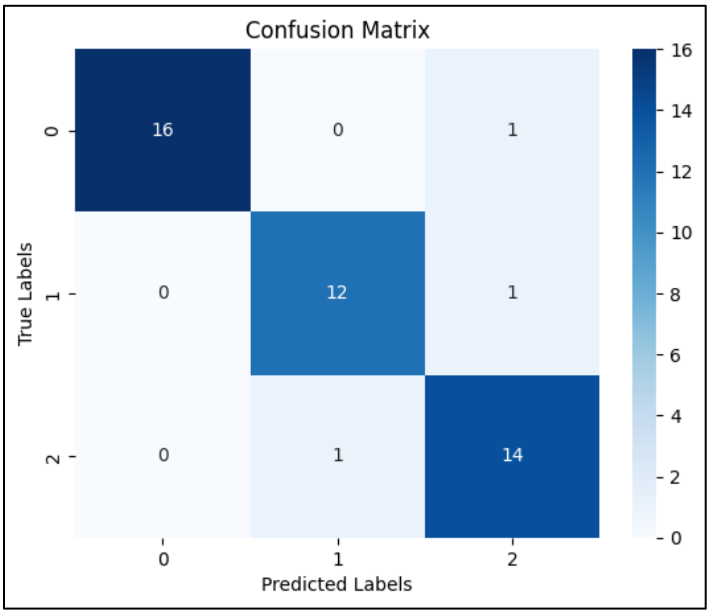

Figure 5. Confusion Matrix of the Ensemble model

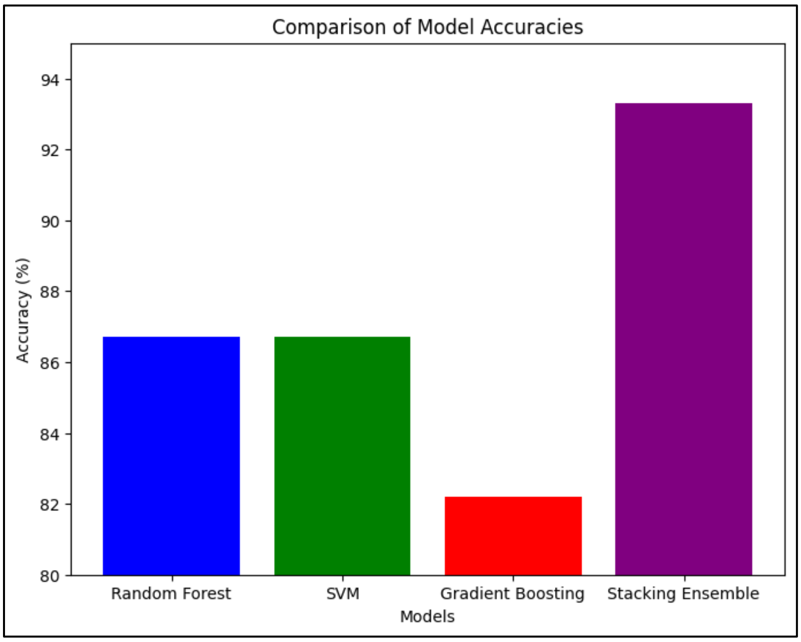

Figure 6. Comparison Histogram for the Models Accuracies

A comparison has been made to understand the results of each model, as shown in Table 2.

Table 2. Performance Metrics of the Models

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	86.6%	0.89	0.87	0.87
SVM	86.6%	0.89	0.87	0.87
GBM	82.2%	0.85	0.82	0.83
Stacking Ensemble	93.3%	0.94	0.93	0.94

Results showed that using advanced ensemble machine-learning techniques was highly effective for classifying leadership styles. Since the Stacking Ensemble model was created using different algorithms, this approach demonstrated high accuracy and described diverse leadership behaviors. The Stacking Ensemble model can be particularly useful for leader assessment.

2) MLP Results Show the distribution of correctly and incorrectly classified leadership levels. Diagonal values indicate correct classifications, while off-diagonal values indicate misclassifications. The "Medium" category had more misclassifications compared to "High" and "Low," as seen in Figure 7.

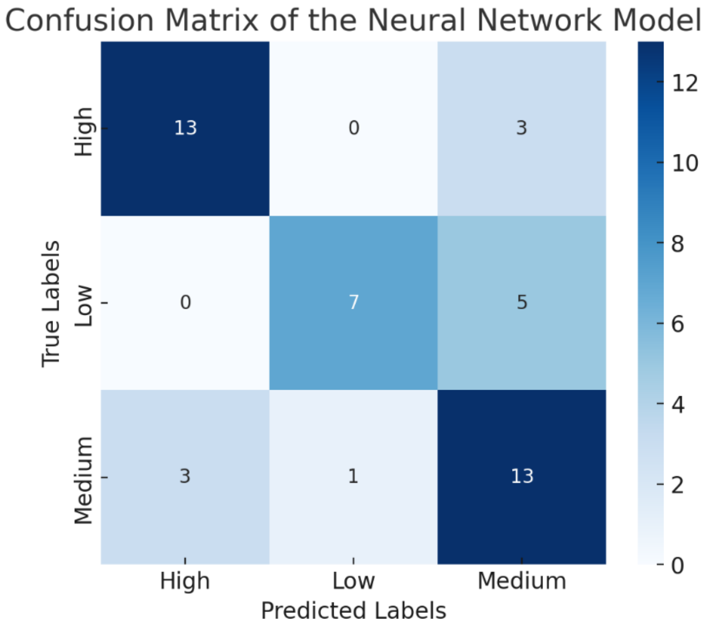

Figure 7. Confusion Matrix of the Neural Network Model

Classification Performance Metrics: A bar chart comparing Precision, Recall, and F1 scores across leadership levels. The "High" category had balanced precision and recall. The "Low" category had high precision but low recall, meaning it was often predicted correctly, but some "Low" cases were misclassified. The "Medium" category had lower precision but higher recall, meaning the model correctly identified most Medium cases but sometimes predicted them incorrectly, as seen in Figure 8.

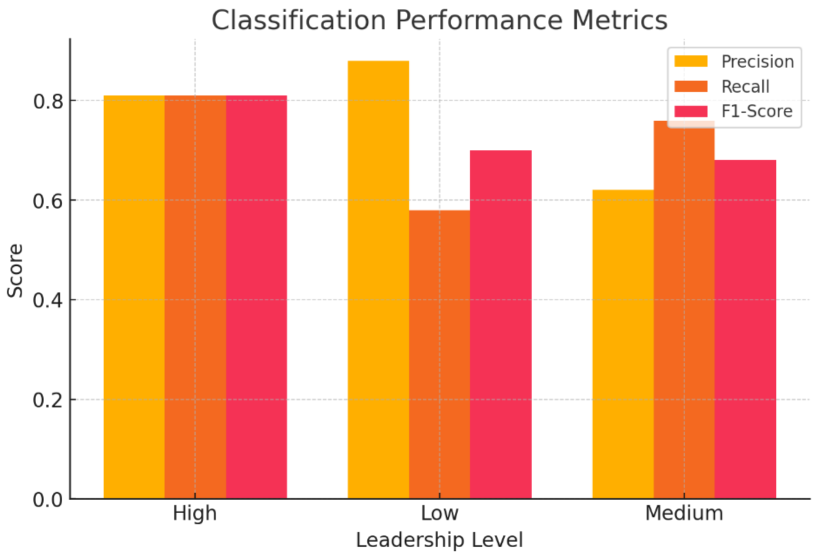

Figure 8. Classification Performance Metrics

3) Performance Comparison of Stacking Ensemble and Neural Network Models To evaluate the effectiveness of different machine learning approaches for leadership classification, we compared the Stacking Ensemble Model with a Neural Network Model (MLP). The results of both models are presented in Table 3.

Table 3. Model Performance Comparison

Metric	Stacking Ensemble Model	Neural Network (MLP)
Accuracy	93.3%	75.6%
Precision	0.94	0.78
Recall	0.93	0.75
F1-Score	0.94	0.77

The Stacking Ensemble Model outperformed the Neural Network Model in all key performance indicators. However, the improved Neural Network Model demonstrated a better classification balance, particularly for the Low and Medium leadership categories.

5. Discussion

The study's outcomes illustrate the effectiveness of ensemble machine-learning solutions for categorizing leadership styles based on behavioral data. The Stacking Ensemble model, which combined results of Random Forest, SVM, and Gradient Boosting, was characterized by 93.3% accuracy, which may be defined as significantly better compared to the results that can be achieved by traditional approaches using a single model. This example illustrates the solution's capacity to interpret multidimensional, complex data and deliver subtype classifications that less sophisticated methods may blur. The findings suggest that the Stacking Ensemble Model provides a more effective solution for leadership classification than the Neural Network Model. The superior performance of the ensemble method can be attributed to its ability to leverage multiple classifiers, effectively mitigating individual model weaknesses.

6. Conclusion

In conclusion, the study developed and validated a Stacking Ensemble machine learning model for classifying Leadership Styles as Low, Medium, and High, with an accuracy of 93.3%. The study further shows that advanced ensemble machine-learning approaches can reasonably interpret complex human behavioral data. The 'ensemble' of machine learners can interpret complex interdependencies between various aspects of leadership and present it understandably to all stakeholders.

The results of the study accordingly have significant practical implications. The study has developed a highly accurate tool that organizations can use to improve their assessments of their leaders. This could lead to a better understanding of leadership dynamics and better leadership development and performance. This tool could also spawn a series of other machine-learning developments that could similarly support HR departments and the organizations they serve. The applications could be far-reaching and transform the process companies assess, define, and develop their leaders. Moreover, the study avidly contributes to the academic discussion of machine learning applications in human resource management and partnership management strategies. The study also develops a practical tool for strategic human resource management. Further study may extend these benefits to practice and test future applications of the tool or tools as described above. Furthermore, his study demonstrates that ensemble learning approaches provide a more effective and interpretable leadership classification method than neural networks. However, deep learning remains a promising direction for further exploration, particularly with larger datasets and enhanced feature engineering.

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Authors declare that there is no conflict of interest regarding the publication of this paper.

Ethical Approval and Informed Consent
It is declared that during the preparation process of this study, scientific and ethical principles were followed, and all the studies benefited from are stated in the bibliography.

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