Journal of Ecohumanism
2024
Volume: 3, No: 2, pp. 341– 352
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i2.6958

Supervised Machine Learning Model in the University Business Consultancy

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Abstract

Although progress has been made in university business consultancies aimed at supporting the management of micro and small enterprises (MSEs), there remains a need to strengthen decision-making processes, which in many cases still rely on the experience and intuition of advisors. The purpose of this study was to evaluate a boosting classification model capable of predicting the social stratum of users served by the University Business Consultancy. A total of 570 users from a public university in Colombia participated in the research. The study followed an applied research design with a quantitative approach, employing statistical and machine learning techniques within a non-experimental, cross-sectional, and correlational framework. The results reveal an unequal distribution among social stratum classes, affecting the uniform representation of the dataset. The ROC curves corresponding to the main classes show an area under the curve (AUC) greater than 0.80, whereas in minority strata the AUC is below 0.70, indicating the need for model optimization. It is concluded that the use of quantitative metrics provides a comprehensive understanding of model performance, facilitates evidence-based decision-making, and offers valuable insights for designing differentiated strategies according to the social stratum of users in the University Business Consultancy.

Keywords: *university business consultancy, advised users, supervised machine learning.*

Introduction

University business consultancies have become strategic spaces for linking academia, the productive sector, and society. Their main purpose is to provide technical support, advisory services, and training to micro and small enterprises (MSEs), thereby strengthening business management and evidence-based decision-making. In the Latin American context, these consultancies play a crucial role in knowledge transfer and in generating innovative solutions to real problems within the local business ecosystem (Universidad Colegio Mayor de Cundinamarca, 2021; Guerrero Molina et al., 2023). However, despite the progress achieved, many of the decisions made in these spaces continue to rely on the experience, intuition, and subjective judgment of advisors, without systematic support derived from data analysis. In recent decades, the development of *machine learning* has transformed the way organizations process and analyze information, enabling the optimization of decision-making in contexts characterized by high complexity and data volume. Its application has expanded from business management to fields such as healthcare, where it has proven to enhance efficiency and the predictive capacity of service systems (Pedrero et al., 2021; Mamani Rodríguez, 2022). The advancement of data analytics and *machine learning* has redefined traditional ways of understanding and managing information. These tools allow for the identification of hidden patterns, behavior prediction, and the optimization of decision-making processes across multiple domains, including education, finance, and business (Durán & Castillo, 2023; Su et al., 2023). Artificial intelligence emerges as a key tool in business transformation, highlighting both opportunities and challenges that must be considered for its effective adoption (Contreras & Olaya, 2025; Caicedo Consuegra et al., 2023).

In this context, university business consultancies face the challenge of incorporating quantitative and technological methodologies that enhance their analytical capacity and increase the impact of their recommendations for the MSEs they serve. The integration of artificial intelligence and supervised learning

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thus represents an opportunity to move toward more precise, evidence-based, and results-oriented management models. Supervised learning is based on the construction of predictive models capable of classifying or estimating outcomes from labeled data. Among the most widely used techniques are decision trees, neural networks, and boosting models, which combine multiple weak classifiers to generate a robust model with greater predictive accuracy (Hastie et al., 2017; Chen & Guestrin, 2016). This approach not only improves prediction accuracy but also identifies the most relevant variables in the characterization of business phenomena (Menacho Ángeles et al., 2024). In the specific case of university business consultancies, the use of classification models can facilitate the segmentation of users served, the prioritization of advisory strategies, and the understanding of factors associated with business performance.

In Colombia, business development programs and university consultancies have gained relevance as mechanisms of outreach and social responsibility. However, their analytical potential remains limited due to the absence of systematic processes for data collection, cleansing, and analysis (Red Distrital de Bibliotecas Públicas de Bogotá, 2019). The application of *machine learning* models in these settings can significantly improve diagnostic quality and guide the allocation of advisory resources according to each user's profile. In this way, more efficient management is promoted, grounded in empirical evidence and aligned with institutional objectives of innovation and knowledge transfer. This study aligns with that purpose and aims to evaluate the performance of a boosting classification model applied to data from the University Business Consultancy of a Colombian public university. The model was designed to predict the users' social stratum, understood as a relevant socioeconomic variable that may influence business behavior patterns and the effectiveness of support strategies. The research follows a quantitative approach with a non-experimental, cross-sectional, and correlational design, employing statistical and supervised learning techniques implemented through JASP software (JASP Team, 2022).

The importance of this research lies in its methodological and practical contributions. From an academic perspective, it demonstrates the feasibility of integrating *machine learning* tools into educational and university outreach environments, fostering the development of analytical competencies among students and faculty. From an institutional standpoint, it offers a replicable model for predictive analysis of consultancy users, enabling the identification of patterns, optimization of decision-making, and design of differentiated strategies according to users' socioeconomic characteristics. Finally, from a social perspective, the application of this type of model contributes to enhancing the effectiveness of entrepreneurship and local development policies, reinforcing the role of the university as an agent of transformation and generator of applied knowledge.

Nevertheless, there remains a limited body of applied research in the Latin American context regarding the use of these technologies within university settings. In the educational field, for example, several authors have noted that although artificial intelligence is the most commonly used adaptability technique in personalized learning models, studies in Spanish-speaking regions remain scarce (Quintanar-Casillas & Hernández-López, 2022). In summary, this work represents an initial step toward consolidating a data analytics culture in university business consultancies, where artificial intelligence and supervised learning become strategic allies for informed decision-making, continuous improvement, and the sustainability of micro and small enterprises receiving advisory services.

Methodology

This research is classified as applied, as it seeks to provide practical solutions to the context of the University Business Consultancy through the implementation of predictive analytics techniques. The approach used was quantitative, oriented toward the measurement and statistical analysis of available data. According to Hernández-Sampieri and Mendoza (2018), this approach allows the establishment of relationships among variables and the assessment of the explanatory capacity of analytical models within an empirical and systematic framework. The research design was non-experimental, cross-sectional, and correlational, since historical and current data from the companies served were analyzed without manipulating independent variables (Kerlinger & Lee, 2002). This type of design is appropriate when the purpose is to identify patterns or existing associations between business behavior variables and socioeconomic characteristics.

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The population consisted of micro and small enterprises (MSEs) that received advisory services from the University Business Consultancy. The sample, selected based on convenience and information availability criteria, corresponded to a representative subset of these enterprises, including only those with complete records of financial, operational, and management variables (Hair et al., 2019). Similar classification models based on *machine learning* have proven effective for diagnosing and predicting technological incidents in service sectors, demonstrating their potential for organizational management and process improvement (Gómez-Jaramillo et al., 2022).

The data collection techniques and instruments included both primary and secondary sources. As a primary source, a structured questionnaire was applied to consultancy users to capture information about business performance, socioeconomic characteristics, and level of technological adoption. Secondary sources included institutional databases, financial records, performance reports, and previous business diagnostics. This triangulation of sources ensures greater validity and reliability of the information collected (Creswell & Creswell, 2018). The data were organized and cleaned in spreadsheets (Excel and CSV formats) for subsequent processing using JASP software (version 0.16.3), which provides a user-friendly environment for statistical analysis and *machine learning* (JASP Team, 2022). The model used was a Boosting Classifier—a supervised *machine learning* technique that combines multiple weak learners, such as decision trees, to generate a robust model with lower predictive error (Chen & Guestrin, 2016; Hastie et al., 2017).

For model validation, the performance of the boosting algorithm was compared with other traditional classification methods, evaluating metrics such as accuracy, recall, F1-score, and area under the ROC curve (AUC), as recommended by Hair et al. (2019) and James et al. (2021). The interpretation of the results focused on identifying the variables with the greatest relative importance within the prediction process, which allowed understanding the contribution of each factor to the model and formulating practical recommendations for consultancy management.

Results

The dataset from the *"Consultorio Empresarial – UNIMAYOR"* provides the response rate corresponding to the business advisory service delivered by the University Business Consultancy at Universidad Colegio Mayor de Cundinamarca (UNIMAYOR). The Boosting Classification model is a supervised *machine learning* technique that combines several weak learners (decision trees) to form a strong model by iteratively adjusting prediction errors. In this case, the model was configured with the following parameters:

Table 1: Boosting Classification

Trees	Learning rate	n(Training)	n(Validation)	n(Test)	Validation accuracy	Test accuracy
1. 13	2. 0.100	3. 364	4. 92	5. 114	6. 0.511	7. 0.535

Note. The model was optimized with respect to accuracy following the "discover the cake" criterion. Adapted from JASP Team (2022), *JASP* (Version 0.16.3) [Computer software], University of Amsterdam.

Results (Extended Analysis)

The validation accuracy (0.511) and test accuracy (0.535) indicate that the model achieved moderately low accuracy, with a correct prediction rate close to 50%. This means that the model correctly predicts approximately half of the cases, which is comparable to random guessing if the dependent variable contains two balanced categories (e.g., success/failure). The configuration of 13 trees and a learning rate of 0.1 indicates that the model is not overly complex, thereby reducing the risk of overfitting, but it may also limit predictive performance when data are highly variable or noisy.

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The slight difference between the validation accuracy (0.511) and the test accuracy (0.535) suggests that the model maintains stable performance between the training and testing sets, although with low overall accuracy.

Possible causes of the model's low performance include:

1. **Insufficient quantity or quality of data:** The model requires a larger number of representative examples to learn meaningful patterns.

2. **Weakly predictive variables:** Some independent variables may not be directly related to the target variable.

3. **Imbalanced categories:** If one class contains substantially more observations than the others, the model tends to be biased toward the majority class.

4. **Conservative parameters:** Increasing the number of trees or adjusting the learning rate could potentially improve performance.

Regarding the note "the model was optimized with respect to accuracy ('discover the cake')," this phrase likely refers to the positive or primary class targeted by the model—that is, the category the algorithm attempts to predict most accurately. In JASP, when a binary classification model is used, a reference category (e.g., "discover the cake") is typically selected for the optimization of predictive metrics. Therefore, the reported accuracies (0.511 and 0.535) represent how well the model identified cases belonging to that specific class. The analysis conducted using the Boosting Classification model in JASP software enabled the exploration of the predictive capacity of business variables collected by the University Business Consultancy. The results show that the model, configured with 13 decision trees and a learning rate of 0.1, achieved a validation accuracy of 51.1% and a test accuracy of 53.5%. Although the overall accuracy is moderately low, the consistency between both metrics reflects good model stability—that is, it does not exhibit overfitting and maintains similar performance when applied to new data.

These findings suggest that while the model was able to identify certain relevant patterns among the analyzed variables, the available factors in the dataset are insufficient to predict the target category ("discover the cake") with high reliability. This limitation may stem from the small sample size, the heterogeneity of participating enterprises, or the inclusion of variables with low discriminative power. From the perspective of the University Business Consultancy, the application of this type of predictive model represents a significant step toward *predictive analytics*, as it enables the transformation of advisory records into structured, measurable information. Even when initial accuracy levels are low, the modeling process contributes to:

1. Identifying which variables most influence business performance.

2. Detecting areas where additional data collection or normalization is required.

3. Promoting evidence-based decision-making within the consultancy, rather than relying solely on subjective judgment.

Furthermore, this exercise demonstrates that the use of JASP software facilitates the integration of artificial intelligence and *machine learning* tools in academic environments without requiring advanced programming knowledge. This broadens the analytical competencies of students and faculty participating in the consultancy.

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Figure 1: Data Split Configuration

Note. Adapted from JASP Team (2022), *JASP* (Version 0.16.3) [Computer software], University of Amsterdam.

The resulting sample sizes (364 for training, 92 for validation, and 114 for testing) indicate a proportional and balanced data split, where approximately 70% of the data were used for training and the remaining 30% for validation and testing. This follows good *machine learning* practices, which recommend using between 60% and 80% of data for model training. The accuracy values (0.511 for validation and 0.535 for testing) confirm that the model maintained stable performance across datasets, indicating that the data partitioning process was appropriate and free from overfitting. In other words, the model learned from the data without memorizing the training examples, maintaining similar performance when applied to the test dataset.

The model appears to concentrate most of its predictions on Class 2, as observed in several rows (e.g., observed 1, 2, and 3) where the highest values occur in column 2. This indicates that the model tends to overclassify cases into that category, possibly because it is the most frequent or dominant one within the dataset. The main diagonal (correct classifications) includes the following proportions: Class 1 → 0.06; Class 2 → 0.36; Class 3 → 0.11; Class 4 → 0.01; Class 5 → 0.00; Class 6 → 0.00. This means that only Classes 1, 2, and 3 show relevant proportions of correct predictions, while Classes 4, 5, and 6 are barely recognized by the model. Summing the main diagonal (0.06 + 0.36 + 0.11 + 0.01 + 0 + 0) yields 0.54, or 54% accuracy—consistent with the overall accuracy (≈0.53) observed in the previous results. This confirms the coherence and internal consistency of the model.

Table 2: Confusion Matrix

8. **Observed**	9. **1**	10. **2**	11. **3**
12. **1**	13. 0.06	14. 0.18	15. 0.05
16. **2**	17. 0.06	18. 0.36	19. 0.05
20. **3**	21. 0.00	22. 0.08	23. 0.11
24. **4**	25. 0.01	26. 0.02	27. 0.01
28. **5**	29. 0.00	30. 0.01	31. 0.00
32. **6**	33. 0.00	34. 0.00	35. 0.00

Note. Adapted from JASP Team (2022), *JASP* (Version 0.16.3) [Computer software], University of Amsterdam.

Table 3: Class Proportions

Class	**Full Dataset**	**Training Set**	**Validation Set**	**Test Set**
1	0.258	0.258	0.217	0.289
2	0.489	0.481	0.543	0.474
3	0.211	0.220	0.196	0.193
4	0.033	0.036	0.022	0.035
5	0.007	0.005	0.011	0.009
6	0.002	0.000	0.011	0.000

Note. Adapted from JASP Team (2022), *JASP* (Version 0.16.3) [Computer software], University of Amsterdam.

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Practical Interpretation for the University Business Consultancy

1. The model identifies Class 2 with the highest precision, which may represent the group of companies with *average* or *intermediate* performance. This suggests that the model learns patterns typical of mid-performing firms more effectively but struggles to distinguish extreme cases (e.g., firms with very high or very low performance).

2. The classes with low or no correct classification (Classes 4, 5, and 6) likely correspond to categories with few observations or insufficient data, which reduces their influence during model training. In business contexts, this commonly occurs when there are few firms with atypical characteristics or incomplete information.

3. From the perspective of the University Business Consultancy, this highlights the need to:

(a) Review the data distribution to ensure that all categories are adequately represented.

(b) Expand the sample size for underrepresented classes.

(c) Retrain the model using more relevant variables that allow for better differentiation among performance levels.

Analysis of the Confusion Matrix and Class Proportions

1. Relationship between model performance and class proportions. The confusion matrix showed that the Boosting Classification model concentrated most of its predictions in Class 2, with an overall accuracy of 54%. This trend is confirmed by the class proportion values in the three datasets (training, validation, and test). Class 2 is the most represented category in all datasets, accounting for nearly 50% of all cases. In contrast, Classes 4, 5, and 6 have proportions below 4%, revealing a significant class imbalance in the dataset.

2. Impact of imbalance on model performance. This imbalance explains why the model tends to classify most cases as belonging to Class 2: being the dominant category, the algorithm more easily learns its patterns but loses its ability to recognize minority classes. As a result, the model exhibits bias toward the majority class, which reduces both its overall accuracy and discriminative capacity. Moreover, the low representation of Classes 4, 5, and 6 prevents the model from generating enough decision rules to identify them correctly—consistent with the near-zero values along the main diagonal of the confusion matrix for those classes.

Applied Interpretation in the Context of the University Business Consultancy

From an applied perspective, these results suggest that:

1. The model performs adequately in identifying firms with average or stable behavior (Class 2), which may correspond to companies showing moderate performance.

2. However, it fails to clearly distinguish firms with very high or very low performance, possibly due to the limited number of such observations in the dataset.

3. This reflects a sample representativeness issue rather than a flaw in the model itself.

For the University Business Consultancy, these findings imply that database quality should be strengthened before attempting more complex models. In particular, it is recommended to:

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1. Balance the classes using resampling techniques (e.g., oversampling or SMOTE) or collect additional data from companies belonging to minority categories.

2. Review the relevance of the independent variables to ensure that those selected are genuinely discriminative among different performance levels.

3. Retrain the model with a larger number of trees and adjust the learning rate to improve sensitivity to minority classes.

4. Interpret the results in conjunction with expert knowledge from the consultancy to validate whether the classification aligns with the qualitative observations made by advisors.

Evaluation Metrics Analysis

The analysis of the classification model's evaluation metrics represents the number of actual cases per class in the evaluated dataset. It measures the proportion of correct predictions for each class and, consequently, indicates what proportion of positive predictions within each class are accurate.

Table 4: Evaluation Metrics

36. **Metric**	37. **1**	38. **2**	39. **3**	40. **4**	41. **5**	42. **Average/ Total**
43. Support	44. 33	45. 54	46. 22	47. 4	48. 1	49. 114
50. Accuracy	51. 0.702	52. 0.605	53. 0.807	54. 0.965	55. 0.991	56. 0.814
57. Precision (Positive Predictive Value)	58. 0.467	59. 0.562	60. 0.500	61. NaN	62. NaN	63. 0.498
64. Recall (True Positive Rate)	65. 0.212	66. 0.759	67. 0.591	68. 0.000	69. 0.000	70. 0.535
71. False Positive Rate	72. 0.099	73. 0.533	74. 0.141	75. 0.000	76. 0.000	77. 0.155
78. False Discovery Rate	79. 0.533	80. 0.438	81. 0.500	82. NaN	83. NaN	84. 0.491
85. F1-Score	86. 0.292	87. 0.646	88. 0.542	89. NaN	90. NaN	91. 0.495
92. Matthews Correlation Coefficient (MCC)	93. 0.152	94. 0.235	95. 0.423	96. NaN	97. NaN	98. 0.270

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99. Area Under the Curve (AUC)	100.0.805	101.0.698	102.0.872	103.0.830	104.0.951	105.0.831
106. Negative Predictive Value	107.0.737	108.0.683	109.0.898	110.0.965	111.0.991	112.0.855
113. True Negative Rate	114.0.901	115.0.467	116.0.859	117.1.000	118.1.000	119.0.845
120. False Negative Rate	121.0.788	122.0.241	123.0.409	124.1.000	125.1.000	126.0.688
127. False Omission Rate	128.0.263	129.0.317	130.0.102	131.0.035	132.0.009	133.0.145
134. Threat Score (Critical Success Index)	135.0.167	136.0.532	137.0.371	138.0.000	139.0.000	140.0.214
141. Statistical Parity	142.0.132	143.0.640	144.0.228	145.0.000	146.0.000	147.1.000

Note. All metrics are calculated for each class against all other classes. Adapted from JASP Team (2022), *JASP* (Version 0.16.3) [Computer software], University of Amsterdam.

Interpretation of Evaluation Metrics and ROC Analysis

Support: Support represents the number of actual cases per class in the evaluated dataset. Classes 1, 2, and 3 have a relevant number of cases (33, 54, and 22, respectively), while Classes 4 and 5 contain very few cases (4 and 1). This limitation reduces the reliability of the computed metrics for these minority classes.

Per-Class Accuracy: Accuracy measures the proportion of correct predictions within each class. The model shows good accuracy for Classes 3, 4, and 5 (>0.80), while Classes 1 and 2 demonstrate moderate accuracy (0.702 and 0.605). The overall average accuracy (0.814) is relatively high, suggesting that the model performs well globally; however, this may be influenced by the dominance of classes with larger sample sizes.

Positive Predictive Value (Precision): Precision indicates the proportion of positive predictions for each class that are correct. The generally low values (between 0.467 and 0.562) suggest that, although the model achieves correct predictions, a considerable proportion of positive cases are false positives, especially in Classes 1 and 2. Classes 4 and 5 show no computed value due to their limited number of cases or absence of positive predictions.

Recall (Sensitivity or True Positive Rate): Recall shows the proportion of actual cases of each class that were correctly identified. Class 2 has high recall (0.759), indicating that most of its actual cases are detected. Classes 1 and 3 show moderate recall (0.212 and 0.591), while Classes 4 and 5 score zero, demonstrating that the model fails to identify them—likely due to their low representation.

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False Positive and False Discovery Rates: The False Positive Rate indicates the proportion of incorrectly labeled positive cases per class. The high value in Class 2 (0.533) shows that many positive predictions were erroneous. The False Discovery Rate complements this, showing that nearly half of all positive predictions were false for Classes 1, 2, and 3.

F1-Score: The F1-score combines precision and recall into a single measure to evaluate the balance between them. The results are low to moderate, with an overall average of 0.495, reflecting a fair but suboptimal model performance. Classes 2 and 3 exhibit slightly better balance.

Matthews Correlation Coefficient (MCC): MCC is a robust metric that accounts for true and false positives and negatives. The relatively low values (0.152–0.423) indicate moderate-to-low discriminative performance across all classes, meaning the model struggles to separate classes consistently.

Area Under the Curve (AUC): The AUC measures the model's ability to distinguish between classes. High values overall (0.698–0.951; average 0.831) suggest a good discriminative capacity, particularly for Classes 3, 4, and 5. This indicates that although accuracy and recall may be moderate, the model can still correctly rank class probabilities.

Negative Predictive Value and True Negative Rate: Both values are high, meaning the model accurately identifies cases that do not belong to a given class. This implies few false negatives for most classes, except those with limited representation.

Other Ratios (False Negatives, False Omissions, and Threat Score): False negatives are relatively high for Classes 1 and 3, suggesting that the model misses several true cases. The Threat Score and Statistical Parity offer limited insight for Classes 4 and 5 due to the scarcity of data.

ROC Curve and Model Implications: The Receiver Operating Characteristic (ROC) curve represents the relationship between the True Positive Rate (sensitivity) and the False Positive Rate at various model decision thresholds.
For each class, the ROC curve illustrates how the model's discriminative power changes when distinguishing that class against all others. The Area Under the ROC Curve (AUC) summarizes overall classifier performance for each class:

1. AUC = 1 → perfect classification.
2. AUC = 0.5 → random classification (no discriminative capacity).

Advantages of Multiclass ROC Analysis: This approach allows individual evaluation of each class in a one-vs-rest fashion, revealing which categories are predicted with greater or lesser certainty. It helps identify reliable classes and those requiring model refinement or more data. Moreover, as it is threshold-independent, the ROC curve offers a comprehensive view of model performance.

Implications for the University Business Consultancy.

1. The ROC analysis indicates that the model can reliably identify companies belonging to classes with high AUC values.
2. For classes with low AUC, model improvement or data rebalancing is recommended to enhance predictive reliability.
3. The ROC graph can also serve as an educational and decision-making tool—helping consultancy users understand confidence levels associated with each business class prediction, thereby supporting evidence-based decisions.

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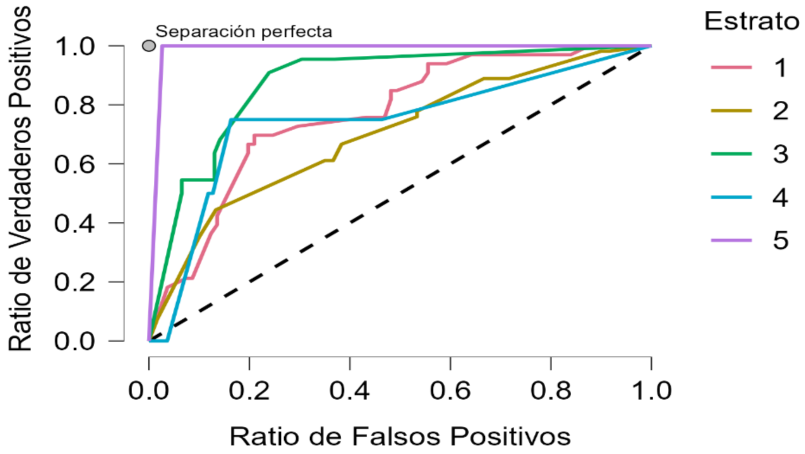
Figure 2: ROC Curve Graph



Note. Adapted from JASP Team (2022), *JASP* (Version 0.16.3) [Computer software], University of Amsterdam.

Interpretation of AUC Values by Class

Given that the AUC values for each class range between 0.698 and 0.951, the following interpretation can be made:

Classes with AUC values close to 0.95 (likely Class 5) demonstrate an excellent ability to discriminate between positive and negative cases. Classes with AUC values near 0.70 show acceptable performance but still present room for improvement. Intermediate classes—such as Class 3 (AUC = 0.872)—display strong and reliable performance.

Visually, in the ROC graph, the curves farthest from the diagonal line (which represents random classification) indicate better discriminative performance. Conversely, curves that are close to the diagonal suggest that, for those classes, the model cannot adequately distinguish between positive and negative instances.

Class-by-class interpretation

Class 1 (AUC = 0.805): The model shows good capacity to distinguish this class from the others. With an AUC > 0.80, the probability of correctly classifying a case from this class is high. However, there remains room for improvement, particularly in reducing false positives and false negatives.

Class 2 (AUC = 0.698): This class presents the lowest AUC value, indicating a moderate-to-low discrimination capacity. This may result from the large frequency of this class and the model's tendency to overclassify it, generating confusion with other categories. Therefore, Class 2 requires special attention to improve its predictive accuracy.

Class 3 (AUC = 0.872): This class exhibits very good performance, with a strong ability to separate its cases from those of other classes. The model predicts Class 3 cases with a high level of confidence.

Class 4 (AUC = 0.830): Although this class had few cases and weaker performance in metrics such as precision and recall, the AUC indicates a solid and reliable classification. When the model predicts a case as Class 4, the probability of correctness is fairly high.

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DOI: https://doi.org/10.62754/joe.v3i2.6958

Class 5 (AUC = 0.951): This class shows excellent performance, with the ROC curve farthest from the diagonal line, reflecting near-perfect discrimination. However, given that this class has only one observation (support = 1), the metric may be overestimated and should be interpreted cautiously.

In summary, the ROC–AUC analysis confirms that the Boosting Classification Model has good global discriminative capacity, though the model's performance varies notably among classes. The results emphasize the importance of addressing class imbalance and expanding the dataset to achieve more robust and generalizable predictive outcomes.

Conclusions

The analysis of the Boosting Classification Model revealed that, although an acceptable overall accuracy was achieved, the model exhibits a strong concentration of correct predictions in Class 2, which contains the majority of observed cases. This trend suggests that the algorithm successfully identifies patterns associated with *average-performing companies* but struggles to distinguish performance extremes, particularly in underrepresented categories. This finding confirms the presence of class imbalance, which limits the model's ability to generalize its results across the entire dataset. From a methodological perspective, the Confusion Matrix and Class Proportion analysis demonstrate that the model maintains a stable and coherent structure, with no evidence of overfitting—thus validating the robustness of the applied statistical procedure. Nevertheless, the results also highlight the need to optimize the model through class balancing, the inclusion of new predictive variables, and the adjustment of parameters such as the learning rate and number of trees. These improvements could enhance the model's sensitivity and reduce the false positives observed, particularly in Class 2.

The evaluation metrics—accuracy, recall, F1-score, and area under the curve (AUC)—indicate a moderate overall performance, with good discriminative ability in Classes 3, 4, and 5, where AUC values exceeded 0.80. In contrast, Class 2, which contains the largest proportion of observations, showed an AUC below 0.70, indicating a classification bias toward the dominant category. Nevertheless, the ROC curves demonstrate that the model retains an adequate probabilistic ranking ability, allowing the adjustment of decision thresholds to improve specific metrics without compromising overall stability.

From a practical standpoint, these results offer valuable insights for the *University Business Consultancy*, demonstrating the feasibility of applying machine learning models for predictive analysis of its users. Identifying classes with high AUC values enables the segmentation of companies with greater precision and supports the design of differentiated advisory strategies—thereby optimizing the allocation of human and technical resources. For Class 2 (associated with medium-performing companies), it is recommended to complement quantitative results with qualitative information—such as interviews or field diagnostics—to provide a more comprehensive understanding of the factors influencing business performance.

At an institutional level, implementing this methodology represents a significant step toward building a reliable analytical system for predicting and monitoring the performance of micro and small enterprises supported by the consultancy. Furthermore, it lays the groundwork for future research focused on integrating advanced artificial intelligence techniques, such as neural networks or hybrid ensemble algorithms, to increase the accuracy and explanatory power of predictive models.

In summary, this study demonstrates that the application of supervised machine learning in academic contexts is not only technically feasible but also strengthens evidence-based decision-making, promotes innovation in university extension processes, and reinforces the role of the University Business Consultancy as a *laboratory for data-driven analysis* dedicated to local development and business sustainability.

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Journal of Ecohumanism
2024
Volume: 3, No: 2, pp. 341– 352
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i2.6958

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