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Influence of Socioeconomic Variables and Skills on the Overall Productivity of a Farm: A Gradient Boosting Based Approach

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Abstract

This study analyzes the influence of several variables on the overall productivity of a farm using machine learning techniques. A Gradient Boosting Regressor model was applied to evaluate the relationship between individual characteristics and productivity, using a quantitative approach. The data were divided into a training (80%) and test (20%) set to ensure reproducibility and evaluate the model using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). The model results indicate that interpersonal skills, age, and education level have a significant impact on productivity, with relative significances of 26.48%, 22.04%, and 20.12%, respectively. The analysis highlights that interpersonal skills are fundamental to optimizing the work environment, while age and education level are correlated with knowledge and experience applied to farm management. On the other hand, variables such as environment, agricultural technician, and administrative accountant did not show a significant influence, probably due to the lack of variability in the data or their lower relevance in the context studied. The findings underscore the need to invest in training and development of interpersonal skills, as well as in continuous training programs to maximize productivity. This study provides data-driven insights that can inform operational strategies and strategic decisions to increase efficiency in farm management. However, limitations were identified in the model, such as low explained variability (R^2 = 0.22), suggesting the need to incorporate new variables to improve future predictions.

Keywords: *Agricultural Productivity, Machine Learning, Gradient Boosting, Socioeconomic Variables, Farm Management, Interpersonal Skills.*

Introduction

Agriculture plays an essential role in the global economy, especially in regions where it represents a primary source of employment and income (Alok et al., 2021). In this context, farm productivity is a key indicator that determines the economic and operational sustainability of farms (Ramesh, 2021). Despite technological and managerial advances, the need to understand how socioeconomic variables and individual skills influence operational efficiency persists.

Existing literature highlights multiple factors affecting agricultural productivity, ranging from technical and climatic aspects to individual employee characteristics (Baig et al., 2022; Baig et

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al., 2023). However, the traditional focus on technical variables often overlooks the importance of interpersonal skills, educational attainment, and demographic characteristics. This gap represents an opportunity to integrate interdisciplinary approaches that address the inherent complexity of farm management.

With the increasing adoption of machine learning techniques in various sectors, agriculture is no exception. These tools make it possible to analyze large volumes of data and discover complex patterns that are difficult to identify using traditional statistical methods, such as Machine Learning (ML) models that can predict crop yields based on historical data and environmental factors, which helps farmers in planning and resource allocation (Jain & Choudhary, 2022). Among the available techniques, the Gradient Boosting Regressor has established itself as a robust model for regression problems, combining predictions from multiple simple models to generate accurate estimates (Brown et al., 2023).

Study Objective

The main objective of this study is to identify the most influential variables in the overall productivity of farms, using an approach based on machine learning. In addition, it seeks to provide an empirical basis to inform strategic decisions, promoting operational efficiency and optimal use of human resources.

Through the analysis of results and the interpretation of the relative importance of variables, we hope not only to contribute to the existing body of knowledge but also to offer practical recommendations that will enable agricultural managers to maximize the productive potential of their operations. This interdisciplinary approach not only has implications for agricultural management but also for the design of policies and vocational training strategies.

Materials and Methods

This study adopted a quantitative approach based on machine learning techniques to analyze the influence of several variables on overall farm productivity. The model selected was Gradient Boosting Regressor (Natekin & Knoll, 2013) widely recognized for its ability to solve regression problems and to capture nonlinear relationships between variables (Gao & Xu, 2024; Nasiboglu & Nasibov, 2022). The dependent variable was overall farm productivity, while the independent variables included interpersonal skills, age, and education level, among other socioeconomic and labor characteristics.

Data were collected from farm operating records, surveys, and the Competea psychometric test, applied to administrative personnel and banana farm owners, and field measurements during a complete agricultural cycle, considering seasonal variations. Subsequently, data processing included cleaning to eliminate outliers, imputation of missing data by interpolation, and normalization of the variables. Categorical variables were transformed into a dummy format for inclusion in the model. The sample was divided into 80% for training and 20% for testing, using a random seed to ensure reproducibility and adequate representation of key characteristics such as age and educational level. In addition, k-fold cross-validation with five partitions was applied to assess the robustness of the model and prevent overfitting.

The Gradient Boosting Regressor was configured using a hyperparameter optimization performed with grid search, adjusting variables such as the number of estimators, maximum tree depth, and learning rate. The performance of the model was evaluated using metrics such as Mean Absolute Error (MAE) (Das, 2024), The Root Mean Squared Error (RMSE) and the

Coefficient of Determination (R^2) (Kuran et al., 2023). The relative importance of the variables was also analyzed to identify their impact on productivity.

Although the model identified important patterns, its explanatory power, reflected in an R^2 of 0.22, suggests that overall productivity is influenced by additional factors not included in the analysis. Variables such as climatic conditions, soil characteristics, technology availability, and specific farm management practices could significantly improve the model if integrated into future studies.

The analysis was performed using Python 3.9 and its specialized libraries such as scikit-learn for modeling, pandas for data manipulation, and matplotlib for visualization of results. The entire analytical process was documented in Jupyter notebooks to ensure reproducibility. Regarding ethical considerations, the confidentiality of the data and the informed consent of the participants were ensured.

While the initial findings are promising, a comparative analysis with other machine learning models, such as Random Forest and Support Vector Machines, is recommended to assess which one provides better results in agricultural contexts. Expanding the size and representativeness of the sample, incorporating data from multiple farms or regions, could provide a more generalizable and robust view of the factors affecting agricultural productivity.

Results

Evaluation Metrics

The model evaluation metrics are presented in Table 1 and indicate that, on average, the model predictions differ from the actual values by approximately 38,884 productivity units. The RMSE, which further penalizes large errors, is approximately 53,528 units. The R^2 value of 0.22 suggests that the model explains approximately 22% of the variability in the overall farm productivity. These results show that, although the model provides some predictive ability, there is a significant portion of the variability in productivity that is not captured by the variables included in this analysis.

Mean Absolute Error (MAE)	**Root Mean Squared Error (RMSE)**	**Coefficient of Determination (R^2)**
38,883.52	53,527.81	0.22

Table 1 Evaluation Metrics

Influence of Variables

The most influential variables on overall productivity were interpersonal skills, age, and level of education, with the relative importance of 26.48%, 22.04%, and 20.12%, respectively, as shown in Table 2; however, the variables "Environment", "Agricultural Technician" and "Administrative Accountant" did not show significant influence on productivity.

Characteristics	**Importance**
Interpersonal	0.2648

Age	0.2204
Instruction	0.2012
Intrapersonal	0.1531
Management	0.1147
Social Skills	0.0205
Sex	0.0200
Task Development	0.0050

Table 2 Influence of Variables on Productivity

Interpersonal skills are fundamental to farm management. The ability of employees to communicate effectively, work as a team, and resolve conflicts contributes significantly to operational efficiency and a positive work environment. Likewise, employee age influences productivity through several mechanisms. Younger employees can bring new ideas and greater energy, while more experienced employees bring knowledge and skills acquired over time.

A higher level of education generally translates into a greater ability to understand and apply advanced farm management techniques, technology, and efficient practices. Intrapersonal skills, including self-management, self-assessment, and motivation, are crucial to individual performance. Managerial skills are essential for planning, organizing, and supervising farm operations.

Although less influential than interpersonal skills, soft skills are still important for collaboration and effective communication within the farm. Promoting a collaborative work environment can have positive effects on morale and productivity. The gender variable has a minor influence on productivity, suggesting that there is no significant difference in productivity based on employee gender. This indicates equal opportunities and capabilities among employees of different genders on the farm.

The variables of environment, agricultural technician, and administrative accountant did not show a significant influence on productivity according to this model. This may be due to the lack of variability in these data or to the fact that these factors are not as determinant as others in the specific context of this farm.

Discussion

The analysis carried out using the Gradient Boosting Regressor model identified the main factors influencing overall farm productivity. Interpersonal skills, age, and educational level stood out as the most important variables, while others such as environment, agricultural technician, and administrative accountant did not show a significant influence. In this section, the implications of these findings in the agricultural context, the limitations of the study, and possible areas of improvement for future analysis will be addressed.

Importance of Interpersonal Skills

The study confirms that interpersonal skills are the most relevant factor for productivity, representing 26.48% of the relative importance according to the model. This highlights the need to prioritize effective communication, conflict resolution, and teamwork within the agricultural work environment. The literature supports this finding, with several studies highlighting the critical role of interpersonal communication, relationships, and intimacy in improving employee performance and overall organizational effectiveness. The following sections elaborate on these findings. (Macwan & Vaghela, 2024) (Nurkholifah et al., 2023).

The practical implications of this finding are clear. Investing in training programs to improve interpersonal skills can result in significant benefits to the organization, as evidenced by several studies that highlight the positive correlation between effective communication and organizational performance (Wahyuni, 2024). These programs not only foster better engagement and collaboration among employees but also improve problem-solving skills, which ultimately leads to better outcomes (Wahyuni, 2024).

Age and Productivity

Age as an influential variable (22.04%) reflects the importance of generational balance in the farms. Younger employees bring energy, innovation, and adaptability to new technologies, while older workers contribute their experience and accumulated knowledge. This balance is essential to create a dynamic environment where the strengths of both groups can be leveraged.

However, this finding also suggests the need for specific policies to manage the workforce. For example, mentoring programs where experienced employees guide younger ones could maximize the synergies between different generations (Pinazo-Hernandis & Sanchez, 2024). These programs foster knowledge sharing, empathy, and a sense of belonging, which ultimately contributes to organizational well-being and productivity (Cai et al., 2021)**.**

Level of Education

Educational level, with a relative importance of 20.12%, underscores the relevance of education on employee performance. More educated workers are better equipped to understand and apply advanced techniques, which can translate into more efficient and sustainable farming practices, such as crop rotation and integrated pest management, which improve soil health and reduce resource use (Abobatta & Fouad, 2024).

To take advantage of this relationship, farms must invest in the continuous training of their personnel. According to Zahra & Mifsud, (2021), education and outreach programs can effectively transform farmers' perceptions and increase their willingness to adopt more sustainable practices. In this sense, farms should prioritize the implementation of courses focused on advanced agricultural technologies, sustainable practices, and efficient resource management strategies, which would strengthen both productivity and operational sustainability.

Variables With Low or No Influence

On the other hand, the model showed that variables such as environment, agricultural technician, and administrative accountant did not significantly impact productivity. This could be due to a lack of variability in the data or to the fact that these variables are not determinant in the specific context analyzed. However, it would be premature to completely rule out their relevance without further studies.

One possible explanation for the low influence of these variables is that aspects such as the environment may already be sufficiently optimized or have an indirect impact not captured by the model. In addition, the absence of certain key variables is likely to have limited the predictive capacity of the analysis. For example, according to Qiao et al., (2022) and Melo et al., (2022), factors such as climatic conditions or soil quality can significantly impact productivity, suggesting that their inclusion could have provided a more complete representation of the dynamics analyzed.

Model Limitations and Analysis

Although the Gradient Boosting model provided a solid basis for the analysis, its results reveal some limitations. The coefficient of determination (R^2) of 0.22 indicates that only 22% of the variability in overall productivity is explained by the variables included in the model. This suggests that there are other factors not considered that also have a significant impact on productivity.

Variables not included that could improve the model include climatic conditions, soil characteristics, technology availability, and specific management practices. Incorporating these variables in future analyses could improve the predictive capability of the model and provide a more complete picture of the factors affecting productivity.

In addition, the size and representativeness of the sample could also have influenced the results. While a sufficiently large sample was used to train the model, including data from multiple farms or regions could provide a more generalizable picture.

Practical Implications

The findings of this study have important practical implications for farm management. First, they underscore the need to focus on human capital development as a key strategy for improving productivity. Initiatives such as training programs, soft skills workshops, and mentoring policies can greatly influence labor performance.

Second, the results highlight the importance of balancing experience and innovation within the workforce. This can be achieved through recruitment and retention strategies that prioritize generational diversity.

Finally, the study emphasizes the importance of continuing education and training. Farms that invest in staff training are better positioned to adopt new technologies and innovative practices, which can increase their long-term competitiveness.

Recommendations for Future Studies

Given the relatively low coefficient of determination of the model, future studies could focus on including additional variables and expanding the data set to improve the robustness of the analyses. In addition, it would be useful to perform comparisons between different machine learning models to determine which provides the most accurate predictions in this context.

Another interesting line of research could be to explore interactions between variables, such as the combined impact of education and interpersonal skills on productivity. These interactions could provide a deeper understanding of the factors that drive labor performance on farms.

Conclusions

This study shows that interpersonal skills, age, and education level are the most influential factors in overall farm productivity. The results underscore the importance of human capital in farm management and highlight the need to invest in training and skills development to optimize labor performance.

The Gradient Boosting Regressor model identified key patterns in the data, although its explanatory capacity was limited. This suggests that productivity is a complex phenomenon influenced by multiple factors, many of which were not considered in this analysis. Future studies should, therefore, incorporate additional variables, such as climatic conditions and technology availability, to provide a more comprehensive and holistic perspective.

The practical implications of these findings are significant. First, farms can improve productivity by implementing training programs that strengthen interpersonal skills and promote continuing education. Second, balancing generational diversity in the workforce can maximize the impact of experience and innovation. Finally, adopting data-driven strategies can help farm managers make more informed and effective decisions.

In summary, this study provides an empirical basis for improving farm management and promoting more efficient and sustainable agricultural practices. However, it also highlights the need for further research on this topic to address the identified limitations and explore new opportunities to increase productivity in the agricultural sector.

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