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Forecasting Coffee Export Values Using Artificial Intelligence: A Comparative Study Between Neural Networks and Decision Trees

Abstract. Brazil is the largest producer and exporter of coffee in the world, and the revenue from these exports has a direct impact on the national economy. Forecasting the monthly price of Arabica coffee represents a strategic tool for producers, exporters, and policymakers. This study compared five machine learning models applied to forecasting the monthly value of Arabica coffee, based on historical CEPEA data from January 1997 to May 2025. The models evaluated were: Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Random Forest, and XGBoost. The MLP and GRU neural networks showed the best performance, with R^2 values above 0.96 and low percentage errors (MAPE < 6.3%), significantly outperforming tree-based models. The results indicate that neural networks are more suitable for modeling financial time series in the context of Brazilian agribusiness.
Keywords: Coffee; Price; Time Series; Artificial Intelligence; Neural Networks

1. INTRODUCTION

Brazil holds a prominent position in the global agricultural landscape, historically being the largest coffee producer and exporter in the world. The coffee crop has profound economic, social, and historical significance for the country, influencing everything from territorial organization to international trade relations. According to the Brazilian Coffee Exporters Council (Cecafé), in 2023 alone, Brazilian coffee exports generated over 6 billion dollars, highlighting the importance of this commodity in the national trade balance and Gross Domestic Product (GDP). As shown in Fig. 1, coffee is produced on a large scale throughout the country, with particular emphasis on the states of Minas Gerais and São Paulo, where a substantial portion of the production is destined for export.

Beyond the export volume, the export value in dollars represents a key factor for the strategic planning of producers, exporters, cooperatives, policymakers, and investors in the sector. Variations in international coffee prices — affected by climatic conditions, exchange rate fluctuations, global supply, and demand — can have significant impacts throughout the production chain. Therefore, accurate forecasting of export prices becomes an essential tool for anticipating risks, optimizing profits, and ensuring greater economic stability for the stakeholders involved.

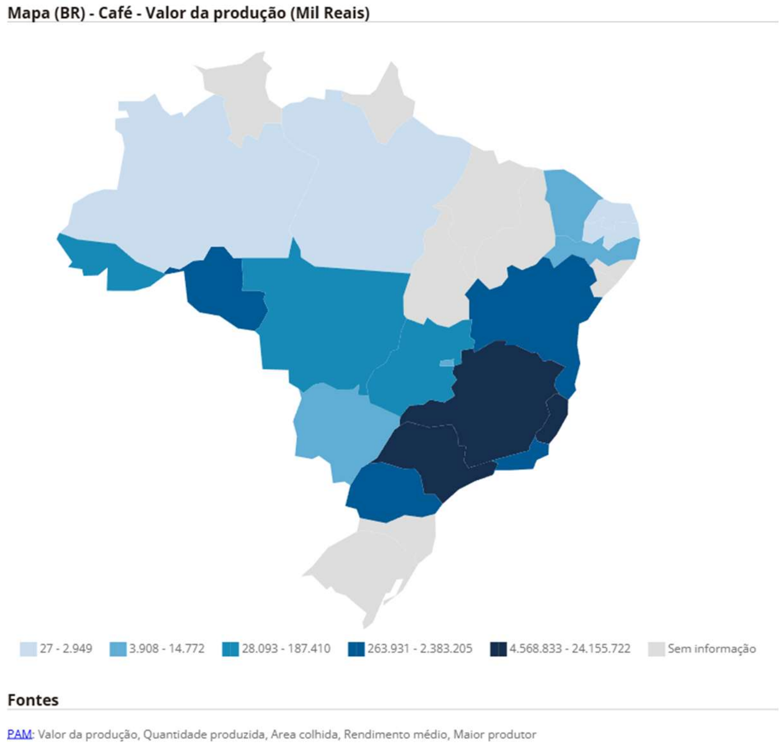

Figure 1 – Production of coffee on Brazil (IBGE, 2025)

In recent years, Artificial Intelligence (AI) has established itself as a powerful ally in the field of predictive analysis, particularly in the context of time series. Models such as Recurrent Neural Networks (RNNs), especially their variants Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), have shown high capability in capturing seasonal patterns and long-term dependencies in financial and agricultural time series. At the same time, simpler architectures such as the Multilayer Perceptron (MLP) continue to deliver strong results under certain configurations.

Beyond neural networks, machine learning algorithms like XGBoost (Extreme Gradient Boosting) and Random Forest have been widely employed due to their robustness, ability to handle nonlinear data, and competitive performance across different forecasting contexts. These models allow the exploration of complex relationships between input variables (such as climate, production, and exchange rates) and export values, making them effective alternatives to support strategic decision-making in the coffee sector. Therefore, this study aims to investigate and compare the performance of these AI models in forecasting the monthly export value of Brazilian coffee, providing a technical analysis of their predictive capabilities and highlighting their potential practical applications for stakeholders in the agribusiness chain.

2. MATERIALS AND METHODS

The data used in this study were obtained from the Center for Advanced Studies in Applied Economics (CEPEA/ESALQ-USP). The dataset comprises the monthly values of Arabica coffee prices in US dollars per 60 kg bag in the Brazilian market, covering the period from January 1997 to May 2025. This time series, consisting of 341 observations, reflects the evolution of prices over time and serves as the basis for the forecasting task. Data preparation included normalization using the MinMaxScaler technique and the construction of temporal windows with lags of 6 to enable the models to learn historical patterns and trends. The series was split into training (70%) and testing (30%) sets, maintaining the temporal order to preserve the sequential structure of the data.

Experiments were conducted in the Jupyter Notebook environment using Python 3.10 as the main programming language. For model development and evaluation, the following libraries were employed: NumPy and Pandas for data manipulation and analysis; Scikit-learn for the

Random Forest Regressor and XGBoost Regressor models, as well as for cross-validation methods and evaluation metrics; TensorFlow and Keras for building and training the MLP, LSTM, and GRU neural networks; and Matplotlib for visualization and graphical analysis of the forecasts. To optimize the performance of each model, a hyperparameter tuning process was performed, which is essential for properly adjusting aspects such as the number of neurons, learning rate, tree depth, and number of estimators. Two complementary approaches were employed: GridSearchCV, which performs an exhaustive search over a predefined space of hyperparameter combinations, and RandomizedSearchCV, which randomly selects combinations within a specified sampling space, allowing greater computational efficiency for larger search spaces. Model performance was evaluated using the Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2).

3. RESULTS

The analysis of the results obtained with the five machine learning models reveals significant differences in terms of performance, accuracy, and generalization capability. The metrics considered — MAE, MAPE, and R^2 — provide a comprehensive view of the effectiveness of each approach for the forecasting task. The MLP model exhibited excellent performance, achieving an R^2 of 0.9691 on the test set, indicating a high capacity to explain the variability of the data. Furthermore, the MAPE of 5.55% suggests a relatively low percentage error, which is desirable in commercial applications. In Figure 2, it can be observed that the MLP-predicted values (orange line) closely match the actual values (blue line).

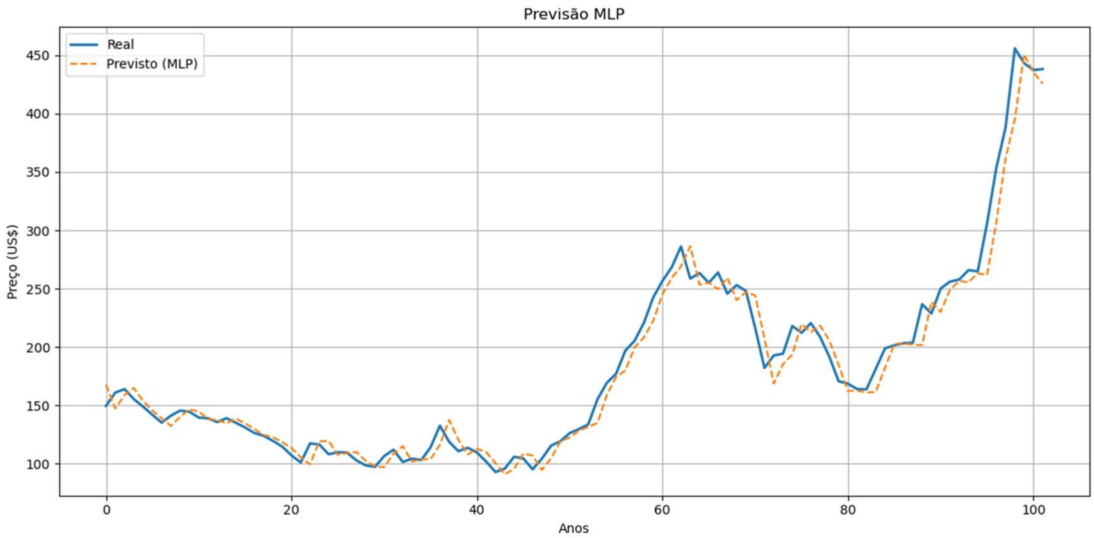

Figure 2 – Comparison between MLP model predictions and actual prices

The LSTM network also achieved highly satisfactory results, with an R^2 of 0.9673 and a MAPE of 6.08%. Although it exhibited a slightly higher error than the MLP, the LSTM stands out for its ability to model longer-term temporal dependencies, which can be useful in scenarios with greater variability or noise in the data. The GRU architecture, on the other hand, achieved the best performance among the neural networks, with an R^2 of 0.9699, slightly surpassing both the MLP and LSTM. Although its MAPE (6.24%) was somewhat higher than that of the MLP, the balance between absolute error, squared error, and coefficient of determination highlights its robustness. In Figure 3, the forecasts generated by the LSTM and GRU models can be observed, respectively.

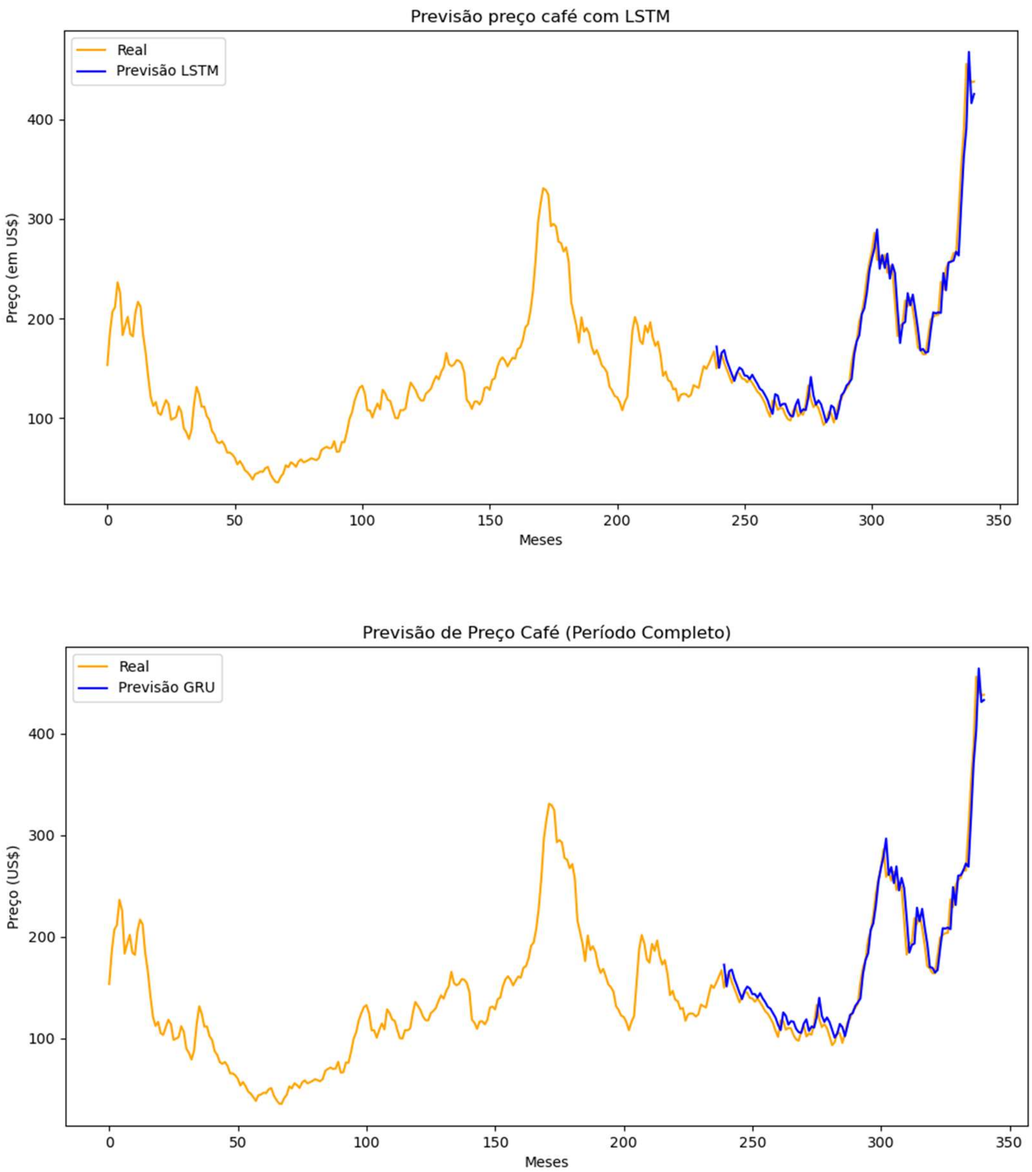

Figure 3 – Comparison of LSTM and GRU model predictions versus actual values

On the other hand, the tree-based models — Random Forest and XGBoost — exhibited lower performance. The Random Forest achieved an R^2 of only 0.8271, with a MAPE of 7.39% and a relatively high RMSE (1165.67), indicating greater variability in the errors. XGBoost showed a slight improvement over Random Forest, reaching an R^2 of 0.8515, but with a MAPE of 8.12%, the highest among all tested models. These results suggest that, although robust, tree-based methods may have limitations when modeling highly dynamic time series such as coffee prices. Table 1 presents a comparison of the metrics across all models.

Table 1 – Comparison between the models

Model	R²	MAE	MAPE (%)
MLP	0,9691	10,14	5,55
LSTM	0,9697	10,92	6,08
GRU	0,9699	10,64	6,24
Random Forest	0,8271	17,12	7,39
XGBoost	0,8515	17,88	8,12

4. CONCLUSIONS

The results highlighted the potential of artificial neural networks, particularly MLP and GRU, in modeling financial time series. The MLP model stood out due to its combination of high accuracy and low percentage error, representing a practical and effective alternative. The GRU, in turn, achieved the highest R^2, reinforcing its ability to handle complex temporal patterns. In contrast, the Random Forest and XGBoost models exhibited lower performance, with higher absolute and percentage errors, indicating less suitability for the type of data analyzed. Although these algorithms are widely used in regression tasks, the results suggest limitations when applied directly to forecasting non-stationary time series such as coffee prices.

Therefore, it can be concluded that neural network-based models are promising tools for supporting decision-making in agribusiness, providing more accurate forecasts that can benefit producers, exporters, and policymakers. Future work may include the incorporation of exogenous variables (such as climate, exchange rates, and international demand), the use of hybrid networks, and evaluation in specific regional contexts, such as the coffee-producing states in Southeast Brazil.

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