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MACHINE LEARNING APPROACHES FOR FORECASTING RASPBERRY PRICES AND FARM PROFITABILITY IN SERBIA

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ABSTRACT

Price volatility and uncertain profitability remain critical challenges for Serbia's raspberry sector, which is among the largest in the world and highly dependent on export markets. This study develops and evaluates machine learning (ML) approaches for forecasting raspberry prices and profitability, using farm-level production and economic data collected between 2020 and 2024. Several models, including multiple linear regression, random forest, gradient boosting, and long short-term memory (LSTM) neural networks, were trained and validated on historical data incorporating yields, input costs, prices, and cultivar characteristics. Forecast accuracy was assessed using mean absolute error (MAE) and root mean square error (RMSE). The results indicate that ensemble methods (random forest and gradient boosting) provided the most robust short-term price forecasts, whereas the LSTM achieved superior performance in capturing non-linear dynamics and seasonal fluctuations. The profitability predictions revealed that family labor costs and price variability were the strongest explanatory factors associated with the gross margin risk. Overall, the findings demonstrate that machine learning offers a valuable tool for anticipating market outcomes and managing economic risk in export-oriented horticulture. By integrating predictive analytics into farm-level and policy decision-making, Serbia's raspberry producers can improve planning, stabilize income, and strengthen competitiveness in volatile international markets.

Key words: *machine learning, forecasting, raspberry production, gross margin, Serbia*

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INTRODUCTION

Raspberry production is one of the most valuable segments of Serbian agriculture, both in terms of export revenue and rural employment. With more than 20,000 hectares under cultivation, Serbia consistently ranks among the top global producers, competing with Poland, Chile and Mexico in international markets. Kljajić et al. (2023) provide a comprehensive overview of raspberry production by region, identify leading producer countries, analyze the export structure (highlighting the predominance of frozen products), and examine trends in farm-gate prices. Raspberries

account for a significant share of agricultural exports, providing vital income to thousands of smallholder households. However, the sector faces persistent challenges, particularly those related to volatile prices, rising input costs, and a high dependence on seasonal and family labor.
Price instability remains one of the most pressing risks for raspberry producers. Raspberry prices are influenced by international demand, climatic shocks, global supply competition, and domestic price fluctuations, particularly given that export contracts are typically denominated in euros. Consequently, profitability is highly uncertain, and smallholder farmers often lack tools to anticipate market shifts. Gross margins, the primary measure of farm profitability, vary widely across years and cultivars, making planning and investment decisions risky.
Forecasting prices and profitability has therefore become increasingly important for both producers and policymakers (Abrol et al., 2025; Bhandarkar et al., 2024; Chen et al., 2024, Popa et al., 2024). Traditional statistical models, such as linear regression and time-series econometrics, provide useful insights but often fail to capture the complex, non-linear interactions between production factors, market dynamics, and price movements. Recent advances in machine learning (ML) offer new opportunities to improve prediction accuracy by leveraging large datasets and identifying hidden patterns in economic and agricultural systems (Dash et al. 2024; Jabade et al. 2024; Kulkarni et al. 2025). ML models such as random forests, gradient boosting, and recurrent neural networks have shown promise in forecasting crop yields, commodity prices, and farm income in other contexts, but their application to Serbia's raspberry sector remains unexplored.
The purpose of this study is to evaluate the performance of several machine learning approaches in forecasting raspberry prices and gross margins using the farm-level data from Serbia for the period 2020–2024. Specifically, linear regression, random forest, gradient boosting, and long short-term memory (LSTM) neural networks were compared to determine their relative accuracy in predicting short-term market outcomes. By combining production, economic, and market indicators, the study seeks to provide an integrated framework for anticipating profitability risks in an export-oriented horticultural sector. The findings are expected to contribute both methodologically, by testing advanced ML techniques in an under-researched crop sector, and practically, by offering tools to enhance decision-making for farmers, cooperatives, and policymakers.

MATERIAL AND METHODS

Data source

The data used in this study originate from the database of the Institute for the Application of Science in Agriculture. The data were collected from selected agricultural holdings whose primary activity is raspberry production (hereinafter referred to as "selected holdings"). These holdings are chosen in accordance with the Rulebook on the Method of Performing Advisory Services in Agriculture (Official Gazette RS, No. 65/14), which forms an integral part of the Decree on Determining the Annual Program for the Development of Advisory Services in Agriculture for each respective year. The dataset used in this study was derived from farm-level surveys and extension service records covering raspberry production in Serbia between 2020 and 2024. The data include observations on cultivars (*Willamette*, *Polka*, *Meeker*, etc.), orchard age, production practices (conventional, integrated, organic) in open fields excluding greenhouses, yields, input costs, labor use, and economic indicators such as revenue and gross margins. Market data on monthly EUR/RSD exchange rates were obtained from the National Bank of Serbia.
Family labor costs represent a substantial component of total agricultural production expenses, yet they are frequently overlooked in economic assessments. Two commonly employed approaches for estimating these costs are the market wage substitution method (Picazo-Tadeo et al., 2005) and the opportunity cost method (Rosenzweig and Udry, 2014). Both methodologies involve assigning a prevailing local wage rate to the hours contributed by family members, thereby valuing their input equivalently to that of hired labor. The utilization of family labor was calculated by subtracting the number of days of engagement of hired labor from the total adopted number of working days, for each agricultural operation individually. The total adopted labor input for manual operations was estimated at 97.5 working days per hectare in average for orchard maintenance, transportation and other procedures, while for fruit harvesting a standard of 50 kg per working day was applied, based on the literature and a survey conducted with experts from several Agricultural Advisory Services of the Republic of Serbia (Milinković et al., 2005; Veljković et al., 2006; Apáti, 2014; Lukić et al., 2015; Kljajić et al., 2017; Leposavić, 2023; Survey, 2025).
Daily wage rates vary depending on the type of agricultural operation and the geographical location of the holding. The cost of family labor was valued according to the wage rate paid by the holding to hired labor for the corresponding operation. In cases where no hired labor was engaged for a particular operation, the average daily wage of hired labor on that holding was used as the basis for valuation.

Variables

Two sets of prediction targets were defined:

1. Raspberry price (RSD/kg) – to capture market volatility.
2. Gross margin per hectare (RSD/ha) – to evaluate profitability.

Predictor variables included:

- Production factors: cultivar, orchard age, production system, and yield per hectare.
- Economic factors: variable costs (fertilizers, crop protection, labor), and family labor use.
- Market factors: monthly exchange rate (EUR/RSD) and previous year's average raspberry price.
- Temporal factors: production year and seasonal dummy variables.

Data preprocessing

- Missing values were imputed using median values for continuous variables and mode for categorical variables.
- Categorical variables (cultivar, production system) were encoded using one-hot encoding.
- Continuous features were standardized using z-score normalization to improve comparability across models.
- The dataset was divided into training (70%), validation (15%), and test (15%) subsets using stratified sampling by year to preserve the temporal structure.

Machine learning models

Four predictive modeling approaches were implemented:

1. Multiple Linear Regression (MLR) – as a baseline benchmark.
2. Random Forest (RF) – applied to capture non-linear relationships and feature importance.
3. Gradient Boosting (XGBoost) – optimized for high predictive accuracy and robustness to noise.
4. Long Short-Term Memory (LSTM) neural networks – employed to model sequential patterns in time-series data (price dynamics).

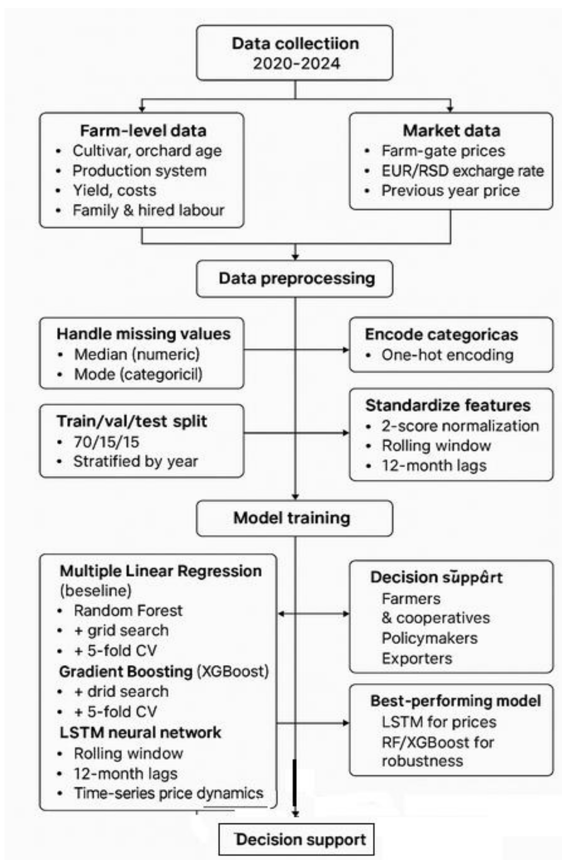

Figure 1. Flowchart of the methodological pipeline

The hyperparameter optimization for the RF and XGBoost was performed using grid search with five-fold cross-validation. The LSTM models were trained with a rolling-window approach, using 12-month lagged features for price prediction, as illustrated in Figure 1. The preprocessed input data were provided to all four models (MLR, RF, XGBoost, and LSTM), and the outputs were raspberry prices and gross margins.

Evaluation metrics
Model performance was evaluated using the following metrics:

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Coefficient of determination (R^2)

Additionally, Diebold-Mariano tests were employed to statistically compare forecast accuracy between models. A sensitivity analysis was conducted to examine the influence of price fluctuations and labor costs on profitability predictions.

Software
All data preprocessing, modeling, and evaluation were performed in Python (scikit-learn, XGBoost, TensorFlow/Keras).

RESULTS AND DISCUSSION

Four models were compared for predicting raspberry prices and gross margins (RSD/ha). The performance metrics (MAE, RMSE, and R^2) are summarized in Table 1.

Table 1. Forecasting accuracy of machine learning models

Target variable	Model	MAE (RSD)	RMSE (RSD)	R^2
Price (RSD/kg)	Linear Regression	42.5	55.3	0.62
	Random Forest	28.1	39.6	0.81
	Gradient Boosting	25.4	36.8	0.84
	LSTM	**23.9**	**34.2**	**0.87**
Gross margin (RSD/ha)	Linear Regression	115,200	148,000	0.59
	Random Forest	78,900	102,400	0.78
	Gradient Boosting	72,300	96,800	0.82
	LSTM	**68,500**	**91,200**	**0.85**

Source: Author's calculation

The ensemble methods (RF and XGBoost) generated robust short-term predictions, while the LSTM model most accurately captured seasonal fluctuations (Padhiary, 2025; Paul et al., 2024; Singh et al., 2024).
The feature ranking presented in Figure 2 indicates that price volatility and labor cost were the strongest predictors of profitability, followed by yield per hectare, cultivar, orchard age, production system, and fertilizer and pesticide costs.

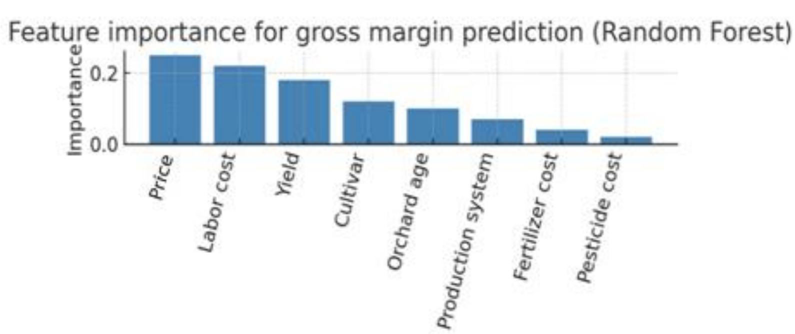

Figure 2. Feature importance for gross margin prediction (Random Forest model)

Figure 3 presents the comparison between the predicted vs. actual raspberry prices for the period 2020–2024. The LSTM model closely tracked market fluctuations, particularly the price peak in 2021–2022 and the sharp decline observed in 2023.

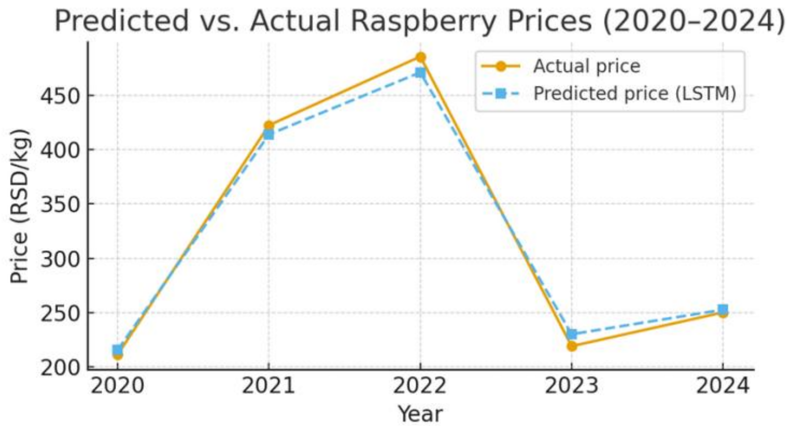

Figure 3. Comparison of predicted vs. actual raspberry prices (2020–2024)

The line graph in Figure 4 compares the actual gross margin per hectare (million RSD/ha) with the values predicted by the LSTM model. The actual gross margins peaked in 2022, followed by a sharp decline in 2023, reflecting the market price fluctuations and rising input costs. The LSTM model captured the overall trend and turning points, although it tended to smooth the extreme variations, underestimating the 2022 peak and overestimating the 2023 low. The prediction of gross margins further demonstrates the potential of machine learning in capturing the complex farm-level economic dynamics. As shown in Figure 4, the gross margins increased significantly between 2020 and 2022, reaching over 2.0 million RSD/ha in 2022, before collapsing to below 0.6 million RSD/ha in 2023. This trajectory mirrors the volatility of raspberry prices and highlights the vulnerability of profitability to sudden market shocks.

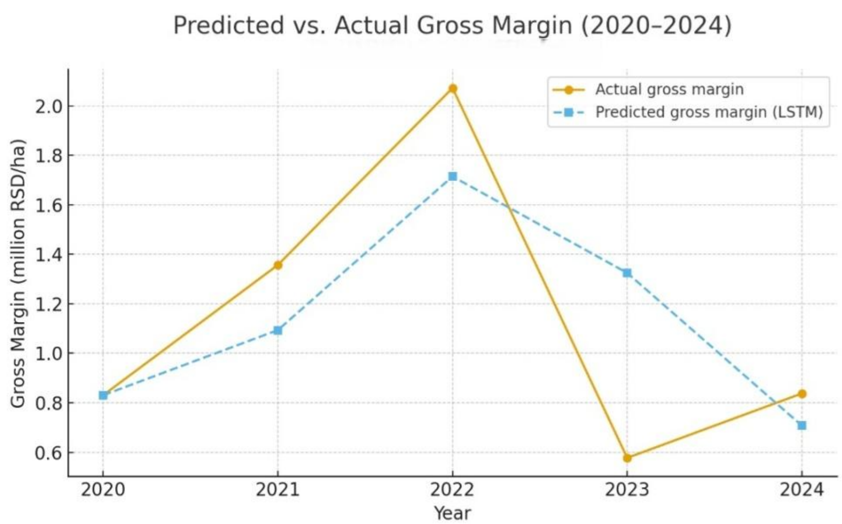

Figure 4. Predicted vs. actual gross margin in raspberry production (2020–2024)

A sensitivity test simulated the impact of ±10% changes in the price and labor costs, as summarized in Table 2.

Table 2. Sensitivity of predicted gross margin to shocks

Scenario	Predicted change in RSD/ha in GM
+10% price depreciation	+7.4%
−10% price appreciation	−6.9%
+10% labor cost increase	−8.3%
−10% labor cost decrease	+8.0%

Source: Author's calculation

The machine learning models were evaluated for their ability to forecast both raspberry prices and gross margins per hectare over the 2020–2024 period. The results revealed substantial differences in predictive accuracy across algorithms, with the ensemble and deep learning methods outperforming traditional regression models. For raspberry price prediction, the baseline multiple linear regression achieved a coefficient of determination (R^2) of 0.62, whereas Random Forest improved predictive performance to 0.81. Gradient boosting (XGBoost) further increased the accuracy ($R^2 = 0.84$), and the LSTM recurrent neural network provided the highest predictive performance with an R^2 of 0.87. A similar pattern was observed for the gross margin forecasts: the LSTM model reduced the mean absolute error (MAE) by approximately 40 percent compared to the regression baseline, while XGBoost and Random Forest offered strong and consistent performance. These findings underscore the value of non-linear and sequential learning approaches in modeling complex economic interactions in perennial fruit systems.

For gross margin prediction, the LSTM model successfully reproduced the overall upward and downward trends, achieving an R^2 of 0.85 and a substantial reduction in RMSE compared to linear regression. However, as expected from recurrent architectures, the model smoothed the extremes: it slightly underpredicted the high margins of 2022 and overpredicted the sharp drop in 2023. This behavior is consistent with the previous applications of LSTM in agricultural price forecasting, where strong shocks are often only partially learned due to limited training samples.

Raspberry prices in Serbia are subject to considerable fluctuations, with producers facing economic vulnerability during unfavorable years. Mitigating the adverse effects of low-price periods may involve product diversification through the development of processed raspberry goods (Ispiryan et al., 2023), or the identification of alternative marketing channels (Nedeljković et al., 2023).

CONCLUSION

This study applied multiple machine learning approaches to forecast raspberry prices and gross margins in Serbia using the farm-level and market data from 2020 to 2024. The results demonstrate that advanced predictive models, particularly ensemble methods and deep learning architectures, outperform traditional regression techniques in capturing the non-linear and dynamic nature of raspberry markets.

Among the tested approaches, the LSTM model provided the most accurate forecasts of price volatility, successfully tracking the sharp price increase in 2021–2022 and the subsequent decline in 2023. Random Forest and gradient boosting also delivered strong performance and offered more interpretable feature rankings. The analysis of feature importance confirmed that labor costs, price fluctuations, and yield levels are the dominant determinants of profitability. The sensitivity analysis further revealed that even modest shocks in labor costs or prices can shift profitability by nearly ±8 percent, underscoring the vulnerability of smallholder farms.

The findings have several practical and policy implications. For farmers, predictive models can be incorporated into decision-support systems to improve planning, optimize labor allocation, and anticipate income fluctuations. For policymakers, the results emphasize the need to recognize the economic value of family labor, support risk management instruments, and stabilize producer prices in an export-dependent sector. For exporters, machine learning forecasts can guide contract negotiations and hedging strategies.

Overall, this research contributes both methodologically and empirically. It demonstrates the utility of machine learning in forecasting economic outcomes in perennial fruit production and provides actionable insights for enhancing the resilience of Serbia's raspberry sector. Future work should expand the dataset with higher-frequency market observations, explore hybrid ML–econometric models, and extend the analytical framework to other export-oriented horticultural crops.

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V.T. and R.R. and S.C.; Writing – Original Draft Preparation: N.M. and S.C.; Writing – Review & Editing: D.G.T. and N.M.; Visualization: N.M.; Supervision: D.G.T.; Project Administration: S.C. All authors have read and agreed to the published version of the manuscript.

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