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Multilayer Perceptron Algorithm for Analyzing and Predicting Cup of Excellence Coffee Pricing: A Data-Driven Approach

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Abstract: *This study investigates the use of a multilayer perceptron (MLP) algorithm to analyze the pricing mechanism of Cup of Excellence (COE) coffee. By incorporating data such as sensory evaluation scores, auction prices, and external market variables, the MLP algorithm provides insights into the determinants of coffee prices. Experiments demonstrate that the proposed model significantly improves price prediction accuracy and reveals patterns linking quality metrics to pricing trends. This paper contributes to the understanding of coffee markets and proposes a data-driven approach for quality-driven price evaluation.*

Keywords: *multilayer perceptron algorithm, COE coffee, machine learning*

1. Introduction

As consumer demand for high-quality coffee continues to grow, the global coffee market is undergoing a quality-driven transformation. Certification competitions like the Cup of Excellence (COE) have played a crucial role in promoting premium coffee. Through rigorous sensory evaluations and international auctions, COE connects high-quality coffee producers with global buyers. However, establishing a scientific pricing mechanism remains challenging due to the multitude of factors influencing coffee prices, including sensory scores, production costs, and international market dynamics[1].

In recent years, machine learning (ML) has emerged as a powerful tool for addressing complex agricultural and economic challenges[2][3]. Its ability to model non-linear relationships and account for multivariate influences has enabled breakthroughs in modeling economic phenomena. Among various ML techniques, the Multilayer Perceptron (MLP) stands out for its superior feature extraction and predictive performance. Studies have shown that MLP effectively handles high-dimensional datasets, uncovering intricate relationships between variables such as coffee variety, climatic conditions, and market trends.

This study explores the application of the MLP algorithm to the COE coffee pricing mechanism by analyzing COE competition data and market trends. The objective is to model the price formation process of premium coffee scientifically. This research not only provides actionable insights for coffee producers and buyers but also offers a scalable framework for understanding pricing mechanisms in other agricultural commodities.

2. Related works

The MLP model has been widely applied in the coffee market, covering multiple fields such as price prediction, quality assessment, and classification. For example, research in 2022 showed that the performance of MLP and Extreme Learning Machines (ELM) in short-term price prediction was significantly better than other methods; research in 2020 utilized MLP to replace manual assessment of coffee quality, effectively reducing costs and biases. Other applications also include the realization of coffee disease detection by combining Convolutional Neural Networks (CNN) with MLP, as well as the optimization of the commodity price prediction framework in complex environments[4-6]. Research also indicates that MLP can integrate key features such as sensory scores, production conditions, and market demands to achieve all-round optimization of pricing and quality assessment. However, despite the MLP model demonstrating characteristics of strong adaptability and good scalability, its applications in niche markets (such as COE) are still relatively few. In particular, the research on combining sensory data with market trends has not been in-depth.

Several studies illustrate the broader application of ML in coffee-related problems, demonstrating its capability to handle non-linear relationships and incorporate diverse features. For instance, research in 2014 utilized MLP and Radial Basis Function (RBF) networks to predict contract prices in the Ethiopian Coffee Exchange (ECX), highlighting the ability of MLP to integrate various market factors and address non-linear dependencies. Similarly, a 2022 study examined the relationship between coffee prices and sensory scores using both SVM and MLP, with the latter proving adept at identifying intricate patterns in price-quality correlations. Another 2022 investigation compared MLP and Extreme Learning Machines (ELM) for short-term coffee price forecasting, concluding that MLP outperformed alternative models in predictive accuracy[7].

Further applications of MLP extend beyond pricing. A 2020 study used MLP to predict coffee quality based on features derived from green and roasted beans, showcasing the model's efficiency in reducing costs and biases associated with human evaluations. In 2023, MLP was also applied in coffee disease classification tasks, where it was evaluated against other classifiers for feature extraction, underscoring its adaptability in agricultural analytics. Research in 2024 compared MLP with traditional forecasting methods such as ARIMA for agricultural commodity pricing, revealing its superiority in capturing seasonal and non-linear trends. Additional reviews in 2024 discussed the role of MLP in coffee classification, including its use in pricing, yield prediction, and quality evaluation. A related framework proposed in 2023 combined MLP with feature engineering for commodity price prediction, emphasizing its scalability and robustness across diverse datasets.

Collectively, these studies highlight several key insights. First, MLP consistently outperforms traditional linear and simpler ML models in capturing non-linear relationships within complex agricultural datasets. Second, its applications extend beyond pricing to include disease detection, quality classification, and yield forecasting. Third, critical features such as sensory scores, production conditions, and external market factors (e.g., global coffee demand) are commonly identified as vital inputs in MLP-based models. Despite these advancements, significant gaps remain, particularly in leveraging MLP to integrate sensory and market data for the COE coffee market. Addressing these gaps offers a promising avenue for future research, with potential applications in price determination, quality control, and production efficiency.

3. Proposed MLP model

To improve the Multilayer Perceptron (MLP) model, several strategies be implemented, focusing on optimization, regularization, and training stability. Incorporating these modifications, such as improved weight initialization, more robust activation functions, and regularization techniques, can significantly enhance the performance and stability of your MLP model. If you're working with larger datasets or deeper architectures, experimenting with different layers, neurons, and optimizer can also yield better results.

3.1. Adaptive Feature Embedding for Coffee Market Data

Traditional MLP models often rely on straightforward one-hot encoding for categorical features and normalization for numerical features. However, this approach can fail to capture nuanced interactions in the data. In our proposed model:

3.1.1. Feature Interaction Embedding

We incorporate a feature interaction layer before feeding the data into the main MLP. This layer models second-order interactions between categorical and numerical features. Given inputs W_{int} (categorical features) and X_{num} (numerical features), the embedding layer computes:

$$\mathrm{H_{embed}} = \mathrm{ReLU}(\mathrm{W_{int}}(\mathrm{X_{cat}} \odot \mathrm{X_{num}}) + \mathrm{b_{int}}) \tag{1}$$

where $\odot$ represents the Hadamard product (element-wise multiplication) W_{int} and X_{num} are trainable weights and biases.

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3.1.2. Dynamic Scaling

Numerical features are dynamically scaled during training using a trainable scaling parameter: α

$$X_{\text{num-scaled}} = \alpha \cdot X_{\text{num}} \tag{2}$$

These mechanisms enable the model to learn feature-specific importance dynamically and improve its capacity to generalize across diverse data distributions.

3.2. Weighted Residual Connections for Price Prediction

To address the complex, non-linear dependencies in coffee price prediction, we introduce weighted residual connections into the MLP structure:

3.2.1. Residual Learning

Instead of passing each layer's output directly to the next, we introduce weighted residual connections that combine the input and output of intermediate layers:

$$\mathrm{H}_{l+1} = \sigma(\mathrm{W}_l\mathrm{H}_l + \mathrm{b}_l) + \beta \cdot \mathrm{H}_l \tag{3}$$

where: $\mathrm{W}_l\mathrm{H}_l$ is the hidden state at layer l, β is a learnable residual weight,σ is the ReLU activation function.

3.2.2. Layer-wise Attention

An attention mechanism is applied to weigh the contributions of intermediate layer outputs to the final prediction:

$$\hat{H} = \sum_{l=1}^{L} \alpha_l \cdot H_l \tag{4}$$

Where

$$\alpha_l = softmax(W_{att} \cdot H_l) \tag{5}$$

These mechanisms enhance the model's ability to handle deep architectures while mitigating vanishing gradient problems.

3.2.3. Mathematical Formulation of MLP

The MLP model is defined as:

$$f(x) = W_o \cdot \sigma_L(\dots \sigma_1(W_1 \cdot x + b_1) \dots) + b_o \tag{6}$$

where: x is the input feature vector, σ represents activation functions (ReLU for hidden lay ers), W_l and b_l are weights and biases of the l_{th} layer.

4. Experimental Results

4.1. Data Description

Data was sourced from COE competition archives, covering over 1,000 samples across multiple years. It included quality scores, producer details, and auction outcomes.

Evaluate the model using metrics such as R2, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE):

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{7}$$

$$\text{RMSE} = \sqrt{\text{MSE}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{8}$$

4.2. Performance Comparison

The experiment compared the performance of the Multilayer Perceptron (MLP) model and a Linear Regression model for predicting Cup of Excellence (COE) coffee prices listed in Table 1. Results demonstrate that the enhanced MLP model outperforms the Linear Regression model across all

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evaluation metrics.

Table 1: Model Performance Comparison.

Model	Mean Squared Error (MSE)	Mean Absolute Error (MAE)	R^2 (Coefficient of Determination)
MLP	0.0058	0.0522	0.9424
Linear Regression	0.0189	0.0988	0.8105

4.3. Prediction Accuracy

4.3.1. Mean Squared Error (MSE)

The MLP model achieved an MSE of 0.0058, significantly lower than the 0.0189 of Linear Regression. This highlights the MLP's ability to accurately capture the relationship between coffee prices and the input features. A lower MSE indicates that the predicted values are closer to the true values, with minimal variance.

4.3.2. Mean Absolute Error (MAE)

With an MAE of 0.0522, the MLP model reduces absolute prediction errors by nearly 50% compared to Linear Regression, which has an MAE of 0.0988. This reflects the MLP's consistency and reliability in coffee price prediction tasks.

4.3.3. Coefficient of Determination (R^2)

The R^2 value for the MLP model is 0.9424, indicating that it explains over 94% of the variance in coffee prices. In contrast, Linear Regression's R^2 of 0.8105 shows limited ability to capture the complexity of the data, suggesting weaker predictive power.

4.4. Analysis and Discussion

4.4.1. Modeling Nonlinear Relationships

The MLP model effectively captures the complex nonlinear relationships between coffee prices and input features through its multilayer architecture and activation functions. COE coffee prices are influenced by sensory attributes (e.g., aroma, taste), market trends, and consumer preferences, all of which exhibit nonlinear interactions that are challenging for Linear Regression to model.

4.4.2. Capturing Multivariate Interactions

The MLP's capacity to handle feature interactions is enhanced by its architecture, which leverages interaction embeddings and weighted residual connections. For example, the interaction between sensory scores and external market trends can modulate pricing dynamics, a nuance that MLP can capture but Linear Regression cannot.

4.4.3. Error Source Analysis

The higher MSE and MAE of Linear Regression suggest limitations in modeling complex relationships and dependencies. The inability to integrate nonlinear features and multivariate interactions results in less accurate predictions. In contrast, the MLP model's deep learning approach addresses these challenges effectively.

The results demonstrate that the improved MLP model significantly outperforms Linear Regression in COE coffee price prediction tasks. By leveraging advanced neural network structures, the MLP model provides superior accuracy and better captures the intricate relationships between quality metrics, market trends, and pricing. These findings validate the potential of MLP for tackling complex, data-driven pricing problems in agricultural markets.

5. Conclusions

This paper demonstrates the efficacy of an MLP algorithm in analyzing and predicting the pricing mechanism of COE coffee. By integrating sensory evaluation and market data, the proposed model not only enhances price prediction accuracy but also provides actionable insights for producers and buyers in the specialty coffee market. Future research could explore incorporating real-time market dynamics

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and expanding the dataset to include broader coffee market trends.

Future research can focus on further optimizing feature engineering and hyperparameters, integrating real-time market data, and extending the framework to other commodities for broader applications.

References

[1] Li J. Research on COE Program with Machine Learning Algorithms [C]. Proceedings of the International Conference on Big Data Economy and Digital Management, 2022.

[2] Sim J, Dixit Y, Mcgoverin C, et al. Machine learning-driven hyperspectral imaging for non-destructive origin verification of green coffee beans across continents, countries, and regions [J]. Food Control, 2024, 156: 110159.

[3] Rodríguez J, Durán C, Reyes A. Electronic nose for quality control of Colombian coffee through the detection of defects in "Cup Tests" [J]. Sensors, 2009, 10(1): 36-46.

[4] Adem M W. Quality control, quality determinants and indication of geographic origin of Ethiopian coffee [D]. Ghent University, 2019.

[5] Worku M, Duchateau L, Boeckx P. Reproducibility of coffee quality cupping scores delivered by cupping centers in Ethiopia[J]. Journal of Sensory Studies, 2016, 31(5): 423-429.

[6] Cascos G, Montero-Fernández I, Marcía-Fuentes J A, et al. Electronic Prediction of Chemical Contaminants in Aroma of Brewed Roasted Coffee and Quantification of Acrylamide Levels [J]. Foods, 2024, 13(5): 768.

[7] Gumecindo-Alejo A L, Sánchez-Landero L A, Ortiz-Ceballos G C, et al. Factors related to coffee quality, based on the "Cup of Excellence" contest in Mexico [J]. Coffee Science, Lavras, v. 16, p. 1-10, 2021.