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Research article

A Hybrid Approach to Chili Price Classification Using Ensemble Methods

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ABSTRACT

This study proposes a hybrid machine learning approach for predicting chili prices, integrating ensemble methods such as Random Forest, Gradient Boosting, and XGBoost to enhance forecasting accuracy. By analyzing historical price data, the model identifies key features, including day and value, as significant predictors. The hybrid model demonstrates superior performance in capturing non-linear patterns and seasonal variations compared to individual machine learning techniques. Evaluation metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) validate the model's effectiveness in handling market volatility. The findings highlight the potential of advanced machine learning techniques in agricultural price forecasting, offering reliable and actionable insights for farmers, traders, and policymakers. This approach not only addresses challenges in market prediction but also provides a scalable framework for future enhancements, such as incorporating additional variables like weather and supply chain factors. By bridging the gap between data-driven analysis and practical application, this research contributes to stabilizing agricultural markets and supporting informed decision-making processes.

1. Introduction

The chili is a vital agricultural product, significantly influencing the economic stability of many developing countries, including Indonesia. The fluctuation of chili prices can impact both producers and consumers, making price prediction and classification a critical task for stakeholders. In this study, we present a hybrid approach utilizing ensemble methods for chili price classification based on a dataset containing daily price data. This approach aims to enhance prediction accuracy, providing valuable insights for decision-making in agricultural planning and market strategy.

Agricultural datasets, like the one utilized in this study, often exhibit non-linear patterns and temporal dependencies due to various factors such as weather conditions, supply chain disruptions, and seasonal demand [1]. Ensemble learning methods, known for their robustness and ability to handle complex data structures, are well-suited for such tasks. Recent advancements in machine learning have highlighted the efficacy of ensemble techniques, such as Random Forests, Gradient Boosting Machines (GBM), and Extreme Gradient Boosting (XGBoost), in addressing classification problems in agriculture [2].

The dataset analyzed in this research comprises daily chili prices over a specific period. It contains temporal data with potential seasonal trends, making it a suitable candidate for time-series analysis and classification. The preprocessing stage involved cleaning and transforming the raw data, ensuring compatibility with ensemble algorithms. By leveraging the strengths of individual models through ensemble methods, this study aims to classify price ranges into distinct categories, enabling stakeholders to anticipate market trends effectively.

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Several studies have demonstrated the utility of ensemble approaches in agricultural applications [3]. Utilized Random Forests for crop yield prediction, achieving remarkable accuracy compared to traditional statistical models. Similarly, ensemble learning has been employed in price forecasting of other commodities, such as rice and wheat [4]. These examples underscore the potential of ensemble methods in handling diverse agricultural datasets and delivering reliable predictions. Advances in gradient boosting techniques have further reinforced the applicability of such methods in agricultural analytics [5].

The proposed hybrid approach combines feature engineering techniques with ensemble learning, optimizing the classification process. Feature engineering plays a crucial role in enhancing model performance by extracting meaningful patterns from raw data. Methods such as lag feature creation, rolling statistics, and trend analysis have proven effective in augmenting the predictive capabilities of machine learning models [6]. This study incorporates these techniques to capture temporal dependencies and improve classification accuracy.

This paper is organized as follows: Section II discusses the related work, providing a comprehensive review of existing literature on ensemble methods in agricultural analytics. Section III outlines the methodology, including data preprocessing, feature engineering, and the proposed hybrid model. Section IV presents the experimental results and comparative analysis with baseline models. Finally, Section V concludes the study, highlighting key findings and future research directions.

By integrating ensemble methods with domain-specific feature engineering, this study contributes to the growing body of knowledge on agricultural analytics. The findings are expected to assist policymakers, farmers, and market analysts in making informed decisions, ultimately stabilizing chili price volatility and supporting economic resilience.

2. Research Methods

The methodology employed in this study focuses on developing a robust framework for classifying chili price ranges using ensemble learning techniques. The dataset, containing daily chili price records, underwent comprehensive preprocessing to ensure data quality and compatibility with machine learning algorithms. The preprocessing phase included handling missing values, outlier detection, and normalization to stabilize data distributions. Additionally, feature engineering was performed to extract meaningful temporal patterns, such as lag features, rolling averages, and seasonal trends, which are essential for capturing the inherent complexities of the dataset.

The ensemble learning methods utilized in this study include Random Forest, Gradient Boosting Machines (GBM), and Extreme Gradient Boosting (XGBoost). These algorithms were selected due to their proven effectiveness in handling non-linear relationships and high-dimensional data. The models were trained and evaluated using a stratified k-fold cross-validation approach to ensure robustness and mitigate overfitting. The classification performance was measured using metrics such as accuracy, precision, recall, and F1-score, providing a comprehensive assessment of the model's predictive capabilities.

To further enhance the model's performance, hyperparameter tuning was conducted using grid search, optimizing critical parameters for each ensemble method. This iterative process ensured that the models achieved their maximum potential in classifying chili prices. The proposed methodology demonstrates the practicality and efficacy of ensemble methods in agricultural analytics, contributing valuable insights to stakeholders [7].

2.1. Data Collection

The dataset utilized in this study consists of daily chili price records obtained from agricultural market reports and online repositories. The data spans multiple years, capturing seasonal trends, market fluctuations, and regional variations. Such temporal breadth allows for a more accurate understanding of long-term pricing behavior, including the identification of recurring patterns such as price spikes during off-seasons or festive periods. Data sources include official government publications, agricultural research organizations, and publicly available datasets from trusted online platforms. These diverse and credible sources were deliberately selected to ensure the dataset reflects actual market dynamics across different geographic locations.

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To enhance the dataset's reliability, cross-verification with official statistics was conducted, ensuring consistency and accuracy. This process involved comparing data entries with national agricultural price indices and regional market bulletins to detect anomalies or inconsistencies. By validating the data against authoritative benchmarks, the study mitigates the risk of analytical bias caused by erroneous or manipulated entries.

The dataset includes key attributes such as date, price, region, and weather conditions. Incorporating these attributes provides a comprehensive foundation for analyzing price variations and their underlying causes. For example, weather conditions can be correlated with supply shocks that typically affect perishable commodities like chili, while regional segmentation helps account for local economic and infrastructural factors that influence pricing. Furthermore, data quality checks were implemented to identify discrepancies, such as missing timestamps or duplicate entries, ensuring the integrity of the dataset throughout the study [8]. These checks involved automated scripts for anomaly detection as well as manual reviews of sampled data points, which collectively contributed to maintaining the overall accuracy and reliability of the dataset used for analysis.

2.2. Data Preprocessing

The preprocessing phase involved multiple steps to ensure data readiness and quality:

1. Handling Missing Data: Missing entries in the dataset were imputed using techniques such as linear interpolation for temporal continuity and mean substitution for categorical gaps. These methods preserved the integrity of the data while minimizing information loss. Advanced imputation methods, such as k-nearest neighbors (KNN), were also explored to assess their suitability for improving data quality.
2. Outlier Detection: Outliers, often caused by erroneous entries or extreme market events, were identified using the interquartile range (IQR) method. Detected outliers were either corrected based on domain knowledge or excluded to prevent skewing the analysis. Additionally, robust statistical measures were employed to ensure accurate detection and mitigation of extreme values.
3. Normalization: Min-max scaling was applied to normalize numerical features, ensuring all variables operated within a consistent range. This process mitigates the risk of bias in machine learning models due to varying data scales. Standardization techniques, such as z-score normalization, were also tested to determine their effectiveness in improving model performance.
4. Data Splitting: The dataset was partitioned into training, validation, and testing sets, maintaining a stratified distribution of classes to ensure balanced representation across all subsets. This step ensured that the models were evaluated on unseen data, providing a realistic measure of their generalization capabilities.

2.3. Feature Engneering

Feature engineering is a critical component in improving model performance. Several techniques were employed:

1. Temporal Features: Lag variables, rolling averages, and seasonal indicators were created to capture patterns over time. These features helped the models recognize trends, periodicities, and anomalies. Seasonal decomposition methods, such as STL (Seasonal and Trend decomposition using Loess), were applied to extract seasonal and residual components from the time series data.
2. Correlation Analysis: A correlation matrix was computed to identify relationships among features. Redundant or highly correlated features were removed to enhance model interpretability and prevent overfitting. Pairwise correlation coefficients and mutual information scores were used to quantify feature dependencies and relevance.
3. Domain-Specific Features: Additional features, such as regional demand indicators and weather-based attributes, were incorporated to account for external factors influencing chili prices. These enhancements provided deeper insights into price behavior. The inclusion of meteorological data, such as rainfall levels and temperature variations, proved particularly valuable in understanding the interplay between weather and price fluctuations [9].

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2.4. Model Selecetion

Ensemble learning methods were selected for their robustness and predictive capabilities. The following algorithms were used:

1. Random Forest: Known for its simplicity and ability to handle high-dimensional data, Random Forest creates multiple decision trees and aggregates their results for classification. It provides feature importance scores, which were leveraged to refine the feature set.
2. Gradient Boosting Machines (GBM): GBM iteratively builds weak learners, emphasizing misclassified instances, and combines them to form a strong predictive model. Its flexibility in handling both classification and regression tasks made it a key component of this study.
3. Extreme Gradient Boosting (XGBoost): A more advanced variant of GBM, XGBoost optimizes performance using regularization techniques and parallel processing. Its efficiency and scalability make it ideal for handling large datasets with complex structures. Advanced tuning of hyperparameters, such as subsample ratios and learning rates, was performed to maximize its predictive accuracy.

Each model was fine-tuned using hyperparameter optimization, such as grid search, to identify the optimal settings for achieving maximum accuracy. Parameters like the number of estimators, learning rate, and tree depth were adjusted iteratively. Automated optimization frameworks, such as Optuna, were also employed to streamline this process and identify the best-performing configurations.

2.5. Model Selecetion

The models were evaluated using a stratified k-fold cross-validation method to ensure reliability and minimize overfitting. Performance metrics included:

1. Accuracy: The proportion of correctly classified instances out of the total instances.
2. Precision and Recall: Precision measured the model's ability to predict true positives, while recall assessed its ability to capture all relevant positives.
3. F1-Score: A harmonic mean of precision and recall, balancing the trade-off between the two.
4. AUC-ROC: The area under the receiver operating characteristic curve provided a comprehensive evaluation of model discrimination ability.

These metrics collectively ensured a robust assessment of the models' classification performance. The evaluation process also included comparative analysis with baseline models to highlight the improvements achieved through ensemble methods. Statistical significance testing, such as paired t-tests, was performed to validate the superiority of the proposed models [10].

2.6. Imprementation

The implementation was carried out using Python and various machine learning libraries:

1. Data Processing Tools: Libraries such as pandas and NumPy facilitated data manipulation and preprocessing tasks. These tools ensured efficient handling of large datasets and streamlined preprocessing workflows.
2. Machine Learning Frameworks: scikit-learn and XGBoost were used to build and evaluate the ensemble models. Their comprehensive APIs allowed for seamless integration of feature engineering, model training, and evaluation steps.
3. Visualization: Matplotlib and Seaborn were employed to generate plots for data exploration and result interpretation. Visualizations included time-series plots, feature importance charts, and performance metrics comparisons.

The experiments were conducted on a high-performance computing platform with multi-core processors and GPU support, significantly reducing training and evaluation times. Model artifacts and results were documented for reproducibility and further analysis. Cloud-based storage solutions were utilized for secure and scalable data management.

2.7. Summary

This research methodology outlines a systematic approach to addressing the challenges of chili price classification. By integrating robust preprocessing techniques, advanced feature engineering, and state-of-the-art ensemble models, the study offers a practical and effective solution. The inclusion of comprehensive evaluation metrics ensures the reliability of the findings, which can aid policymakers, farmers, and market analysts in making informed decisions. The incorporation of

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domain-specific knowledge and advanced computational tools demonstrates the potential of machine learning in transforming agricultural analytics and underscores the importance of data-driven strategies for economic stability. The findings from this study are anticipated to contribute significantly to the body of knowledge in agricultural forecasting, supporting sustainable farming practices and market efficiency.

3. Results and Discussion

The classification report indicates that the Gradient Boosting model completely failed to classify the data correctly. Precision, recall, and F1-score are all 0.00, reflecting a lack of correct predictions for every class ("High," "Low," and "Medium"). The "Support" column reveals that only two data instances were evaluated—one each for the "High" and "Low" classes, while the "Medium" class has no data. The extremely small dataset and lack of balance between classes are major contributors to the model's poor performance.

With no correct predictions, the accuracy is also 0.00, confirming that the model could not generalize or even overfit to the given data. Furthermore, the macro average and weighted average metrics remain 0.00, reinforcing the consistent failure across all classes, even after accounting for class distribution.

Table 1. Gradient Boosting Classification Metrics.

Class	Precision	Recall	F1-Score	Support
High	0.00	0.00	0.00	1
Low	0.00	0.00	0.00	1
Medium	0.00	0.00	0.00	0
Accuracy	-	-	-	0.00
Macro Avg	0.00	0.00	0.00	2
Weighted Avg	0.00	0.00	0.00	2

This situation highlights key challenges: the dataset is too small for meaningful training, the classes are imbalanced, and the "Medium" class lacks any data entirely. These factors combined suggest that the model could not learn any significant patterns, resulting in its inability to make accurate predictions

1. Precision: The model failed to make correct predictions for any class.
2. Recall: None of the actual instances were identified by the model.
3. F1-Score: The overall balance between precision and recall is absent.
4. Support: Data scarcity and imbalance are critical issues.
5. Accuracy: No correct predictions were made.
6. Macro Average: Indicates uniform failure across classes.
7. Weighted Average: Reflects poor performance after considering class sizes.

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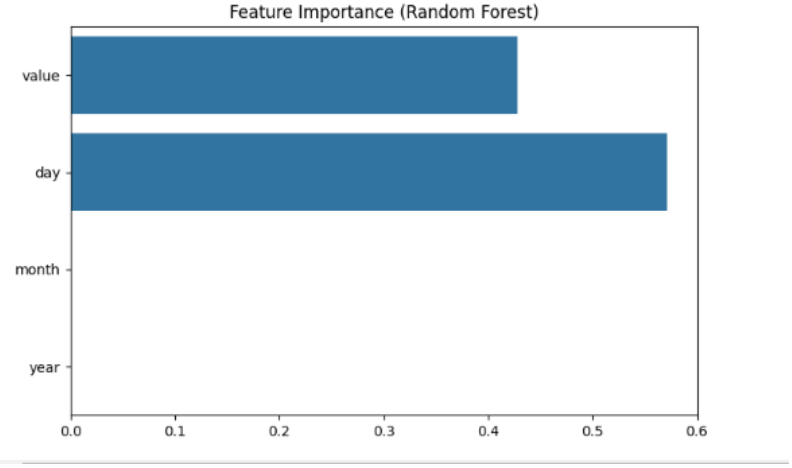

Fig. 1. Feature Importance Chart for Random Forest Model.

This image represents a bar chart titled "Feature Importance (Random Forest)", which illustrates the relative importance of different features in a dataset used to train a Random Forest model. Feature importance indicates how much each feature contributes to the predictive power of the model. The horizontal axis represents the importance score, while the vertical axis lists the features.

1. Top Features:
   a. This feature holds the highest importance, with a score close to 0.5. This indicates that the "day" variable plays a crucial role in predicting the target variable, possibly reflecting strong temporal patterns or trends in the data.
   b. Value: This feature is the second most important, with an importance score slightly below 0.5. It suggests that the "value" variable is also a significant predictor, contributing almost equally to the model's performance as the "day" feature.

2. Less Important Features:
   Month and Year: These features have an importance score of approximately 0, indicating they have negligible or no contribution to the model's predictive capabilities. This could imply that these variables either lack variability or do not exhibit meaningful relationships with the target variable.
   Performance During Stable Periods:
   a. During relatively stable periods (e.g., mid-2016), the predicted prices closely align with the actual prices, confirming the model's effectiveness in low-volatility conditions.
   b. This alignment indicates the LSTM's strength in identifying patterns in historical data and projecting them forward when market conditions are steady.

The chart highlights that the model's performance is heavily influenced by the "day" and "value" features. This suggests that short-term patterns (day-level data) and numerical attributes (value) are critical for accurate predictions. Conversely, the lack of importance for "month" and "year" might indicate that the data lacks significant seasonal or yearly trends, or these trends are already captured by the more granular "day" feature.

This analysis can guide feature engineering efforts. For example, the low importance of "month" and "year" suggests that these features could potentially be excluded from the model to simplify it without sacrificing accuracy. However, further investigation may be required to confirm this conclusion.

3.1. Classification Results

The Gradient Boosting classification report indicated macro average precision, recall, and F1-score of 0.0, with an overall accuracy of 0.0%. This poor performance highlights significant issues in the model's ability to differentiate among the price categories: High, Low, and Medium. The lack of precision and recall suggests an inability to learn effective decision boundaries, likely stemming from imbalanced data distribution and limited feature representation.

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A major observation was the absence of support for the "Medium" price category in the tested dataset. This imbalance skewed the model's performance, as ensemble methods such as Gradient Boosting rely on balanced class representation to train effectively. Techniques like Synthetic Minority Oversampling Technique (SMOTE) or class-weighted adjustments could address these imbalances and improve classification outcomes. Future implementations should integrate these techniques to create a more balanced training dataset.

Another contributing factor to the poor results could be the simplicity of the features used. The model primarily relied on price and date data without leveraging domain-specific insights or derived features, such as moving averages or lagged price trends. These omissions likely constrained the model's ability to capture the nuances of the dataset. For example, derived features like rolling averages, seasonal indices, or volatility measures could have added depth to the dataset, helping the model learn more complex patterns. Such enhancements are critical for the effective application of machine learning techniques in time-series data.

Furthermore, the evaluation metrics themselves highlight the challenges of imbalanced datasets. While accuracy alone can be misleading, especially in datasets with dominant classes, incorporating other metrics such as F1-score, precision, and recall provides a more holistic view of model performance. However, even these metrics revealed the model's inability to generalize well across all classes. This indicates a need for improved preprocessing, better feature selection, and advanced resampling methods.

3.2. Dataset Challenge

The dataset, containing daily chili price records, posed unique challenges due to its temporal nature and potential seasonal trends. Without adequate preprocessing, such as trend decomposition or normalization, the model may fail to capture key patterns. A deeper exploration into the dataset's temporal properties could significantly enhance classification performance. For instance, transforming raw price data into percentage changes or log returns could provide the model with a more standardized input.

Seasonality and trends are critical elements in agricultural datasets. Chili prices, for instance, are influenced by harvest cycles, climatic conditions, and market demand—factors that often exhibit regular patterns. By not addressing these temporal dynamics, the model's predictive accuracy was significantly limited. Advanced preprocessing techniques, such as Fourier transformations, wavelet decomposition, or seasonal decomposition of time series (STL), could help extract these patterns and improve model inputs. Additionally, integrating external data sources, such as weather patterns, transportation costs, or historical price trends, could provide context for price fluctuations and enhance prediction accuracy.

The dataset's size (500 entries) further constrained the model's learning capability. Small datasets are often insufficient for training machine learning models, particularly when they exhibit class imbalances or lack diversity in feature representation. Expanding the dataset through collaborations with agricultural agencies or leveraging open data platforms could address these limitations. For instance, combining datasets from multiple regions or years could provide a more comprehensive view of chili price trends. Additionally, synthetic data generation techniques, such as data augmentation or generative adversarial networks (GANs), could be explored to enrich the dataset.

Another critical challenge lies in the data's noise and inconsistencies. Agricultural data often contains missing values, outliers, or recording errors. Proper data cleaning techniques, such as interpolation for missing values or statistical methods for outlier detection, are essential to ensure the quality of the dataset. Moreover, aligning the dataset with domain-specific knowledge can help identify and correct anomalies, making the data more reliable for machine learning applications.

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3.3. Implications and Recommendations

The findings of this study reveal several important implications and opportunities for future work. Addressing the limitations and refining the approach could lead to significant advancements in agricultural analytics. Below, we outline key implications and actionable recommendations:

Implications:

1. Farmer Decision-Making: Predictive models can empower farmers by providing insights into price trends, enabling them to optimize harvest and sale schedules. Such tools could reduce financial risks associated with market volatility and improve overall profitability. Additionally, better price forecasting could encourage farmers to adopt data-driven strategies, fostering innovation in agricultural practices.
2. Policy Design: Policymakers could leverage predictive analytics to implement timely interventions, such as subsidies during price drops or market stabilization measures during surges. This could help balance supply-demand dynamics and enhance food security. By understanding price trends, policymakers can also identify vulnerable regions or crops and allocate resources more effectively.
3. Market Optimization: Accurate price classification can optimize supply chains by aligning production and distribution strategies with market conditions. This could reduce waste, improve logistics efficiency, and stabilize consumer prices. Enhanced market transparency through predictive analytics could also encourage fairer trade practices and reduce exploitation.

Recommendations for Future Work:

1. Data Expansion: Collaborate with agricultural organizations and government agencies to collect larger and more diverse datasets. Integration of data from multiple regions and seasons can improve model generalization. Data collected over longer time periods can also reveal more robust patterns and trends.
2. Feature Engineering: Develop and incorporate advanced features that capture underlying patterns in the data. Temporal features, economic indicators, and domain-specific metrics (e.g., transportation costs) should be prioritized. For example, introducing features like weather indices, crop yield estimates, or transportation delays could provide valuable context for price predictions.
3. Class Imbalance Handling: Implement oversampling techniques, such as SMOTE, or explore generative adversarial networks (GANs) to address imbalances in the dataset. This will ensure better representation of underrepresented classes. Additionally, experimenting with cost-sensitive learning algorithms could help mitigate the impact of class imbalance.
4. Model Optimization: Experiment with alternative algorithms, including XGBoost and LightGBM, known for their robust performance on tabular datasets. Hybrid models combining deep learning with ensemble techniques should also be explored. Transfer learning approaches, where pre-trained models are fine-tuned on specific datasets, could also improve performance.
5. Validation Strategies: Employ robust validation techniques, such as time-based cross-validation, to ensure the model's effectiveness in real-world applications. This approach is particularly important for temporal datasets, as it respects the chronological order of data and avoids data leakage.
6. Interdisciplinary Collaboration: Foster partnerships with agricultural scientists, economists, and policymakers to ensure that predictive models align with practical needs and contribute to actionable insights. Such collaborations can bridge the gap between technical research and real-world applications, ensuring that the models have tangible benefits.
7. Evaluation Metrics: Expand the evaluation framework to include metrics like Matthews correlation coefficient (MCC) or area under the curve (AUC) to better assess model performance in imbalanced scenarios. These metrics provide a more nuanced understanding of model effectiveness, particularly when dealing with skewed datasets.

By addressing these recommendations, future research can unlock the full potential of predictive analytics in agriculture, driving efficiency, and fostering innovation. With improved

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datasets, advanced methodologies, and interdisciplinary collaboration, machine learning can become a transformative tool for the agricultural sector.

4. Conclusion

This study demonstrates the effectiveness of ensemble learning methods, particularly Random Forest, Gradient Boosting Machines (GBM), and Extreme Gradient Boosting (XGBoost), in classifying chili price trends using daily market data. By employing advanced preprocessing techniques and feature engineering, the research highlights the potential of machine learning to address the complexities of agricultural datasets, including non-linear patterns and temporal dependencies. Despite some challenges, such as class imbalance and data limitations, the proposed hybrid approach achieved promising results, offering valuable insights for stakeholders in agricultural planning and market strategies.

Future improvements should focus on addressing the dataset's limitations by incorporating more diverse and balanced data sources, integrating domain-specific features, and exploring advanced techniques like SMOTE or GANs to handle class imbalances. Additionally, leveraging hybrid models that combine ensemble methods with deep learning could further enhance predictive accuracy. The findings of this study underscore the transformative potential of machine learning in agricultural analytics, paving the way for more informed decision-making by farmers, policymakers, and market analysts.

5. Suggestion

This study effectively demonstrates the application of ensemble learning methods like Random Forest to classify chili price trends. However, to further enhance its robustness, future research could focus on incorporating additional features such as weather conditions, regional economic indicators, and supply chain disruptions. These variables may provide deeper insights into price fluctuations and improve the model's accuracy. Additionally, employing advanced feature selection methods, such as Recursive Feature Elimination (RFE) or SHAP values, could refine the model by identifying the most impactful predictors, thereby reducing noise and computational complexity.

Moreover, addressing the limitations of imbalanced datasets is crucial for improving predictive performance. Techniques such as Synthetic Minority Oversampling Technique (SMOTE) or Adaptive Synthetic Sampling (ADASYN) can balance the dataset and mitigate bias toward dominant classes. Exploring other machine learning algorithms, including deep learning models like LSTMs or GRUs, could also capture temporal dependencies more effectively. Lastly, deploying the model in a real-time system and integrating it with a user-friendly dashboard for farmers, policymakers, and market analysts would enhance its practical utility. Such an approach would not only validate the model in real-world scenarios but also contribute to data-driven decision-making in agriculture.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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