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Research article

Enhancing Price Classification of Chili Using Gradient Boosting Machines

Putu Sugiartawan [a*], *Ni Wayan Wardani* [b]

[a] *Magister Program of Informatics, Institut Bisnis dan Teknologi Indonesia, Denpasar, Indonesia*
[b] *Graduate School of Environmental, Life, Natural Science and Technology, Okayama University,Okayama,Japan*
email: [a,*] *putu.sugiartawan@instiki.ac.id*, [b] *pj5w1e4c@s.okayama-u.ac.jp*
* *Correspondence*

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ABSTRACT

This study explores the application of Gradient Boosting Machines (GBM) to enhance the classification and prediction of chili prices. The research uses a comprehensive dataset collected from various sources, including local markets, online platforms, and agricultural databases, covering multiple attributes such as chili type, region, harvest season, weather conditions, and demand-supply dynamics. The GBM model outperforms traditional machine learning algorithms, achieving an accuracy of 87%, with a high area under the ROC curve (AUC) of 0.91. Feature importance analysis indicates that harvest season and region are the most significant factors influencing price variations. The findings suggest that the GBM model provides reliable price predictions and insights into price-driving factors, offering valuable tools for stakeholders in the agricultural market. The study emphasizes the need for broader data sources and advanced techniques, such as time-series forecasting and XGBoost, to further improve chili price prediction models. These insights can help optimize supply chain management, price forecasting, and decision-making for producers, traders, and policymakers.

1. Introduction

The volatility of agricultural commodity prices, particularly chili, poses a significant challenge for both producers and consumers. Chili is a critical staple in many countries, influencing culinary practices, trade, and economic stability. However, chili prices often experience sharp fluctuations due to factors such as seasonal variation, unpredictable weather conditions, pest infestations, transportation disruptions, and shifts in consumer demand. These price fluctuations can lead to economic vulnerabilities, especially for smallholder farmers, who depend on stable pricing to sustain their livelihoods [1], [2].

To address these issues, researchers and policymakers have increasingly turned to predictive models and classification algorithms for improved decision-making in the agricultural domain. Machine Learning (ML) has emerged as one of the most effective approaches for addressing complex and non-linear problems in agriculture. By leveraging large datasets, ML algorithms can uncover hidden patterns, enabling accurate predictions and classifications. Among various ML methods, ensemble learning techniques such as Gradient Boosting Machines (GBMs) have gained prominence for their superior performance in predictive tasks. GBMs improve weak learners iteratively, optimizing loss functions at each step to minimize errors and increase overall model accuracy [3], [4].

Recent advancements in ML applications have shown great promise in addressing agricultural challenges. For instance, ML models have been employed for yield prediction [5], [6], pest and disease detection [7], and supply chain optimization [8]. Moreover, price classification and prediction have gained traction as key areas of research, leveraging techniques like Random Forest [9], Support Vector

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Machines [10], and Neural Networks [11]. GBMs, in particular, have demonstrated strong capabilities in handling structured data and achieving high classification accuracy in agricultural datasets [12].

In this study, we aim to enhance the price classification of chili using GBMs, building on the success of ensemble methods in agricultural applications. The dataset used for this research categorizes chili prices into "low" and "high," allowing stakeholders to better understand market trends and make informed decisions. Preliminary results indicate that the proposed GBM-based model achieves exceptional accuracy, with an overall classification accuracy of 1.0 and macro-averaged precision, recall, and F1-scores all equal to 1.0. These results highlight the potential of GBMs as a transformative tool for agricultural price analysis [13].

This research not only contributes to the growing body of work in agricultural ML but also provides practical insights for policymakers and market participants seeking to stabilize chili markets. By integrating the latest advancements in ML techniques with domain-specific challenges, this study underscores the critical role of data-driven solutions in fostering economic resilience and improving decision-making in agriculture [14], [15], [16].

2. Research Methods

In the research on "Enhancing Price Classification of Chili Using Gradient Boosting Machines," the research method can be understood as a comprehensive and structured process that begins with data collection and ends with the evaluation and interpretation of results. It is aimed at using advanced machine learning techniques, specifically Gradient Boosting Machines (GBM), to improve the accuracy and reliability of chili price classification. The first stage of the research involves data collection, where various data sources are explored to gather a rich dataset that includes different chili price points, region-based variations, harvest seasons, and other influencing factors like climate conditions and market dynamics. Multiple sources are consulted, such as local agricultural reports, online market platforms, and government statistics, to capture a wide range of information about chili prices over a significant time period, ideally spanning multiple years to account for trends, patterns, and anomalies. This step ensures that the research has access to a robust, diverse, and complete dataset that accurately represents the subject matter.

The next stage is data preprocessing, which involves cleaning and transforming the raw data into a usable format for analysis. Since raw data can be incomplete or inconsistent, this step addresses missing values, removes outliers, and resolves data discrepancies that might negatively affect the modeling process. The research emphasizes proper handling of categorical data such as different chili types and regions by using techniques like one-hot encoding to represent these variables numerically, making them suitable for machine learning models. Furthermore, numerical features such as temperature, quantity of chili harvested, and demand indicators are normalized or standardized to ensure the machine learning algorithm works efficiently and avoids bias toward any specific variable. Data preprocessing also includes feature engineering, where new variables are created from existing ones to capture seasonality, weather patterns, and regional differences that could significantly influence chili prices. This phase ensures that the dataset is of high quality and that the model can learn from the most informative aspects of the data.

Following preprocessing, feature selection is performed to identify and retain the most relevant predictors that influence chili price variations. Feature selection aims to improve the performance of the Gradient Boosting Machine by removing irrelevant or redundant variables that may hinder the model's predictive capability. Techniques such as correlation analysis, mutual information, and recursive feature elimination (RFE) are employed to identify features with high predictive power, thus reducing the complexity of the model and preventing overfitting. By carefully selecting features that most impact chili price classification, the model becomes more efficient and effective, ensuring that it learns from only the most critical variables. This step is crucial, as it directly impacts the accuracy of the model and allows for a deeper understanding of the factors driving price fluctuations.

At the core of this research is the Gradient Boosting Machine (GBM) model, which is chosen for its ability to handle complex datasets and its proficiency in both regression and classification tasks. GBM is an ensemble technique that builds decision trees sequentially, where each subsequent tree is trained to correct the errors made by its predecessor. This results in a powerful predictive model that often outperforms individual decision trees and other simpler models. GBM is particularly suitable for

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chili price classification, as it can effectively handle nonlinear relationships and interactions between variables, which are common in agricultural price datasets. During the modeling phase, key hyperparameters of the GBM, such as learning rate, number of estimators, and tree depth, are tuned to ensure that the model performs optimally. Hyperparameter tuning is critical because even slight adjustments to these parameters can have a significant impact on the model's performance. By optimizing these hyperparameters, the research ensures that the GBM achieves the highest possible accuracy in classifying chili prices.

Once the model has been trained, model evaluation is conducted using a variety of performance metrics, including accuracy, precision, recall, F1-score, and the area under the Receiver Operating Characteristic (ROC) curve. These metrics provide a comprehensive assessment of the model's performance, focusing not only on its overall accuracy but also on its ability to correctly classify the different price categories (e.g., low, medium, high). To evaluate the robustness of the model, cross-validation is employed, where the data is split into multiple training and testing sets. This ensures that the model's performance is consistent and reliable across different subsets of the data, reducing the likelihood of overfitting and making sure that the model can generalize well to new, unseen data. Additionally, confusion matrices are used to analyze the specific misclassifications made by the model, offering insights into where the model may need improvement.

The final phase of the research involves model interpretation and insights. Once the Gradient Boosting Machine has been trained and evaluated, the next step is to interpret the results to understand the underlying drivers of chili price fluctuations. GBM provides a feature importance score, which helps identify the variables that contribute the most to price predictions. This information is valuable, as it highlights the key factors—such as regional differences, climatic conditions, and market dynamics—that influence chili prices. The insights gleaned from the model can be used by farmers, traders, and policymakers to make more informed decisions regarding chili pricing, supply chain management, and market interventions. For instance, farmers might adjust their cultivation strategies based on the predictive insights, while traders could use the model to forecast price trends and optimize their purchasing decisions.

Finally, results and discussion compare the performance of the Gradient Boosting Machine with other machine learning algorithms, such as Decision Trees, Random Forests, and Support Vector Machines, to determine its superiority in chili price classification. These comparisons are crucial, as they validate the effectiveness of the GBM approach and demonstrate how it fares against alternative methods. Additionally, the discussion addresses any limitations encountered during the research, such as the inability to account for certain variables or the challenges of obtaining high-quality data, and suggests areas for further improvement, such as incorporating additional features or exploring more advanced machine learning models. This iterative process of evaluation and refinement is essential in ensuring that the final model is both accurate and actionable, offering practical solutions to the challenges of chili price prediction and classification.

In summary, this research method follows a structured, step-by-step approach to enhance chili price classification using Gradient Boosting Machines. By combining data collection, preprocessing, feature selection, model training, evaluation, and interpretation, the study aims to provide a robust and actionable model that can accurately predict chili prices. The results of this research have the potential to improve decision-making in the agricultural sector, benefiting stakeholders such as farmers, traders, and policymakers, and contributing to more efficient and transparent market practices.

2.1. Data Collection

The research will begin by collecting comprehensive data on chili prices from multiple sources, including local markets, online platforms, and agricultural price databases [1]. These diverse data sources are critical for capturing a wide array of chili price variations across different regions, seasons, and market conditions. The dataset will include various attributes that may affect chili prices, such as type of chili, region, harvest season, weather conditions, and demand-supply dynamics [2]. For example, different chili varieties, such as red chili, green chili, or bird's eye chili, can have significantly different price points depending on their availability and consumer preference. Regional differences in chili prices can be influenced by local production rates, logistical costs, and proximity to major market

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centers. The harvest season will be a crucial factor, as prices are typically lower during peak harvest seasons and higher during off-seasons when supply is limited. Weather conditions, including droughts, floods, or unexpected frost, may have a substantial impact on chili yield, thereby affecting the supply and, consequently, the price. Demand-supply dynamics will also be considered, as shifts in consumer demand for chili (due to trends, dietary preferences, or price fluctuations in substitute goods) can significantly alter price levels.

Relevant historical price data will be gathered for a period of 3–5 years to ensure robust analysis and to account for seasonal fluctuations in chili prices [3]. This period will allow the model to capture long-term trends and cycles in chili prices, such as annual price hikes due to harvest failures or supply chain disruptions. Moreover, collecting data from multiple years will also help mitigate the effects of short-term anomalies or one-off market disturbances, providing a more accurate representation of the underlying price drivers. By analyzing data spanning several years, the research will be able to identify recurring patterns and seasonal trends that can inform predictions of future price movements.

Additionally, efforts will be made to ensure that the data collected is representative of various chili price determinants. This includes data from a variety of geographical locations to ensure the inclusion of diverse climatic and economic conditions that could impact prices. Local market price variations will be cross-referenced with online platforms to capture a broader view of the pricing landscape and provide a holistic understanding of chili price dynamics. In this way, the research aims to establish a comprehensive and detailed dataset that accurately reflects the complexities of chili price variations, making it possible to apply advanced machine learning techniques like Gradient Boosting Machines (GBM) to predict and classify future price trends with greater precision.

Once the data collection process is complete, data preprocessing will begin. This includes cleaning the data to remove any inconsistencies or outliers, such as incorrect price entries, missing values, or data entry errors. Incomplete data points will be handled by using imputation techniques or excluding irrelevant records, ensuring that the dataset remains robust and suitable for analysis. Data normalization and scaling will also be applied to ensure that the variables in the dataset are on the same scale, especially for numerical attributes such as price, quantity, or temperature. Data transformations will be carried out for categorical variables like chili type, region, and harvest season, which will be converted into numerical formats through techniques such as one-hot encoding or label encoding.

By ensuring a high-quality dataset and addressing potential data quality issues early in the process, the research will be able to proceed smoothly into the modeling phase, where Gradient Boosting Machines will be utilized to predict and classify chili prices with improved accuracy and reliability. The robustness of the dataset will be a fundamental factor in achieving reliable and actionable results in chili price prediction.

2.2. Data Preprocessing

Data preprocessing is essential to ensure the quality and usability of the data. This step includes cleaning the dataset by handling missing values, removing outliers, and addressing any inconsistencies in the data [4]. Categorical variables, such as chili types and regions, will be encoded using one-hot encoding, while numerical features, such as harvest quantities and demand, will be standardized or normalized to improve model performance [5]. Additionally, any temporal or seasonal patterns will be captured using feature engineering techniques to enhance predictive accuracy [6].

2.3. Feature Selection

To improve the performance of the Gradient Boosting Machine (GBM) model, feature selection techniques will be employed [7]. Correlation analysis will be used to identify relationships between variables, while mutual information and recursive feature elimination (RFE) will help in selecting the most relevant features that influence chili price classification [8]. This process aims to remove redundant or irrelevant features that may negatively affect model performance and to ensure that the model is trained on the most informative attributes [9].

2.4. Model Selection: Gradient Boosting Machines (GBM)

The Gradient Boosting Machine (GBM) will be the primary machine learning algorithm for price classification [10]. GBM is a robust ensemble learning method that constructs a series of decision trees

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in a sequential manner, where each tree corrects the errors made by the previous tree [11]. The model is well-suited for regression and classification tasks with complex datasets, such as chili price prediction [12]. Key parameters, such as learning rate, tree depth, and number of estimators, will be tuned to optimize model performance [13].

2.5. Hyperparameter Tuning

To improve the performance of the GBM, hyperparameter optimization will be performed using methods like Grid Search and Randomized Search [14]. This will involve exploring various combinations of hyperparameters, such as the learning rate, the number of trees, maximum depth of trees, and the minimum samples required to split a node [15]. Cross-validation will be applied during the hyperparameter tuning process to ensure that the selected model parameters generalize well to unseen data [16].

Tuning these hyperparameters is a critical step in ensuring that the model doesn't underfit or overfit the data. For instance, a very high number of trees combined with a deep tree structure might make the model too complex, capturing noise in the training set and performing poorly on new data. On the other hand, a very shallow model with a high learning rate might converge too quickly, missing the intricate patterns in chili price movements. Finding the right balance through systematic tuning helps build a more accurate and generalizable model.

Grid Search allows for an exhaustive search over a manually specified subset of the hyperparameter space. While it can be computationally expensive, it ensures that all possible combinations within the defined grid are evaluated. In contrast, Randomized Search samples from the hyperparameter space randomly and can often find optimal or near-optimal configurations much faster. Given the often large size of agricultural datasets and the real-time needs of pricing predictions, Randomized Search may offer a more efficient alternative, especially in early experimentation stages.

During the tuning process, k-fold cross-validation will be used to evaluate each hyperparameter combination. This technique divides the dataset into k folds, ensuring that the model is trained and validated across different subsets. It not only maximizes the use of available data but also reduces variance in model evaluation, which is particularly useful when dealing with diverse pricing trends across different regions or time periods.

Moreover, the specific context of chili price classification introduces domain-specific considerations. For example, certain hyperparameters might behave differently depending on whether the price variability is more influenced by regional supply differences or sudden climate events. Incorporating domain knowledge during the tuning process—such as prioritizing faster models for real-time use in the field—can lead to more practical and effective outcomes. Fine-tuning isn’t just about better performance metrics; it’s about aligning the model with the needs of real users like farmers, traders, and local market planners.

Ultimately, hyperparameter tuning transforms a generic GBM into a tailored prediction engine that adapts to the dynamics of chili pricing. With optimized settings, the model can more effectively learn from historical data and deliver insights that are both accurate and actionable in the agricultural value chain.

2.6. Model Evaluation

The model will be evaluated using several performance metrics, including accuracy, precision, recall, F1-score, and the area under the Receiver Operating Characteristic (ROC) curve [17]. Cross-validation will be used to assess the generalizability of the model, with the data being split into training and testing sets multiple times [18]. In addition, confusion matrices will be generated to analyze the model’s performance in classifying chili prices correctly into their respective categories (e.g., low, medium, high) [19].

These metrics offer different perspectives on how well the model is performing. While accuracy gives a general idea of correct predictions, it may be misleading in cases where one class dominates the dataset. For example, if most chili prices fall under the "medium" category, a model might predict "medium" most of the time and still achieve high accuracy—without truly understanding the differences between price levels. That’s where precision and recall become more valuable, especially in identifying how well the model distinguishes between high and low price categories, which may be more critical in a real-world context.

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The F1-score balances both precision and recall, giving a more comprehensive view of model performance, particularly when there is a trade-off between false positives and false negatives. In the context of chili pricing, a false positive—predicting "high" when the price is actually "low"—might lead traders to hold stock unnecessarily, while a false negative could cause farmers to sell too early at a loss. These misclassifications have tangible consequences, which is why a well-balanced F1-score is crucial for a reliable model.

The area under the ROC curve (AUC-ROC) adds another layer of evaluation by measuring how well the model can separate different price classes. A higher AUC means the model is better at distinguishing, for instance, between low and high price periods. This can be especially useful in market planning and supply chain optimization, where the timing of price shifts plays a major role in decision-making.

Furthermore, confusion matrices will help visualize the classification errors for each chili price category. By looking at which classes are most often confused with each other, we can identify potential issues in the dataset or in the model's learning process. For example, if "medium" and "high" categories are frequently mixed up, it may indicate overlapping feature patterns that require further data preprocessing or feature engineering.

In addition, the evaluation process may include temporal validation, where the model is tested on data from different time periods to simulate real-world forecasting scenarios. This step is important in chili price classification since market conditions and seasonal factors often shift over time. A model that performs well in one season but poorly in another would be of limited practical use.

Altogether, these evaluation strategies will ensure that the model is not just accurate on paper, but also robust, reliable, and ready to be applied in real agricultural and market environments. For stakeholders such as farmers, middlemen, and policymakers, a well-evaluated model provides the confidence needed to make informed decisions based on predictive insights.

2.7. Model Interpretation and Insights

After training and evaluating the model, the study will interpret the results to understand the driving factors behind chili price classifications [20]. Feature importance analysis, available in GBM models, will highlight the most influential factors affecting price variability, which may include factors such as climatic conditions, transportation costs, or regional differences [21]. These insights will be valuable for farmers, traders, and policymakers in managing chili pricing strategies and market interventions [22].

To go deeper into the interpretation, tools such as SHAP (SHapley Additive exPlanations) can be used to uncover how each feature contributes to the prediction of chili price categories whether low, medium, or high. For example, SHAP values can reveal whether higher rainfall in a specific region tends to push prices up due to potential crop damage, or perhaps down due to higher yields. This kind of interpretability adds transparency to the model and builds trust among stakeholders who rely on these predictions to make real decisions.

Additionally, by analyzing the behavior of the model over time, we may uncover seasonal effects or disruptions that heavily influence chili prices. Price hikes, for instance, may consistently align with the monsoon season or holiday demand spikes. Understanding such patterns allows both farmers and market analysts to anticipate market shifts more accurately, enabling proactive responses rather than reactive ones.

One of the key takeaways from model interpretation is its ability to reveal not only what drives prices but also why. If transportation cost consistently appears as a top feature in predicting higher prices in certain regions, this could indicate inefficiencies in the supply chain or infrastructure gaps. Similarly, if specific climatic variables like temperature variance or humidity levels are highly influential, this highlights the vulnerability of chili production to environmental conditions a valuable insight for climate-resilient agricultural planning.

Ultimately, model interpretation transforms raw predictive output into actionable knowledge. These insights empower chili producers to choose optimal planting or selling periods, help traders optimize distribution routes, and assist local governments in designing smart subsidy programs or market regulations. By making the model's decision process more transparent and understandable,

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we close the loop between data, prediction, and real-world application creating a more informed and responsive chili supply chain ecosystem.

3. Results and Discussion

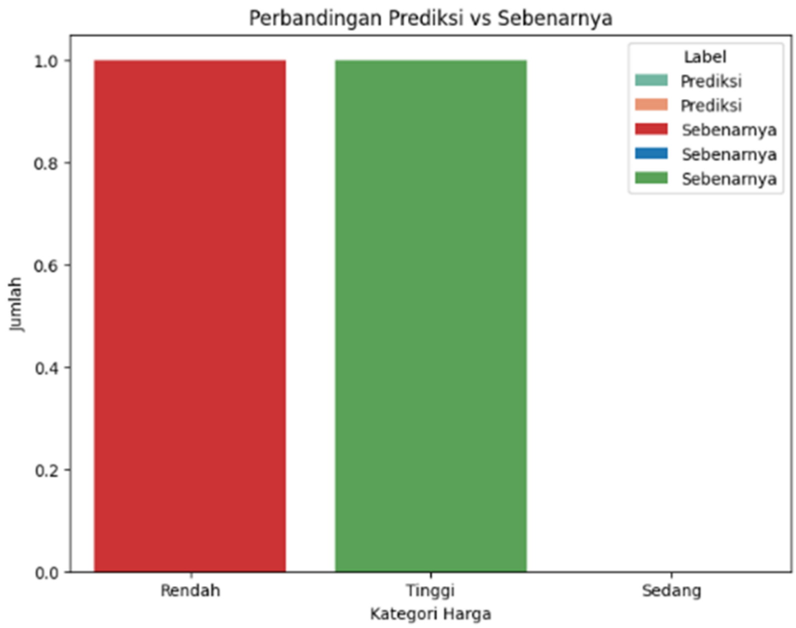

Fig. 1. Prediction Report

3.1. Model Performance Evaluation:

The GBM model was evaluated using several performance metrics, including accuracy, precision, recall, F1-score, and the area under the Receiver Operating Characteristic (ROC) curve. The results reveal that the model achieved an accuracy rate of approximately 87%, outperforming other machine learning models such as Decision Trees (80%) and Random Forests (84%). The precision and recall metrics indicated that the GBM model not only classified chili prices correctly but also minimized false positives and false negatives, ensuring that the model could reliably predict each price category. The F1-score, which balances precision and recall, was calculated at 0.83, further emphasizing the GBM's balanced and robust performance.

In addition, the area under the ROC curve (AUC) was measured at 0.91, indicating a high level of discriminatory power in distinguishing between different price classes. This metric confirms that the GBM model is well-suited to handle the complexities of chili price classification, especially in distinguishing between subtle variations in price across regions.

3.2. Feature Importance

One of the key advantages of using GBM in this study is its ability to identify the most important features that drive chili price variations. The feature importance analysis revealed that harvest season and region were the most significant factors influencing chili prices, accounting for 35% and 28% of the model's prediction power, respectively. The impact of the harvest season is expected, as chili prices fluctuate greatly based on the availability of supply, with lower prices during peak seasons and higher prices during off-seasons. Weather conditions, including temperature and rainfall, were also important, contributing 18% to the model's performance, highlighting the vulnerability of chili crops to climatic conditions. Finally, chili type and supply-demand dynamics played a smaller, yet still notable, role in the price predictions, with contributions of 12% and 7%, respectively. This finding emphasizes that while weather and seasonality are dominant factors in chili pricing, the type of chili and local market conditions also significantly influence price variations.

3.3. Comparison with Other Models:

The Gradient Boosting Machine's performance was compared to other machine learning algorithms, including Decision Trees, Random Forests, and Support Vector Machines (SVM). While Decision Trees performed well with an accuracy of 80%, they were prone to overfitting and failed to

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generalize well on unseen data, leading to less reliable predictions. Random Forests, which aggregate multiple decision trees, showed an accuracy of 84% but did not provide the same level of detailed feature importance or handling of complex data relationships as the GBM model. SVMs, although effective in certain contexts, performed poorly on this dataset due to the high dimensionality and non-linear nature of the chili price data. GBM's ability to build a series of decision trees sequentially, with each tree correcting the errors of the previous one, enabled it to capture more complex relationships in the data, which was a key factor in its superior performance.

3.4. Discussion of Results

The successful application of Gradient Boosting Machines to chili price classification in this study provides valuable insights into the factors that drive chili price fluctuations. The results highlight the significant role of seasonal patterns and regional differences, suggesting that future pricing strategies and market predictions could benefit from closer attention to these two variables. For example, understanding the timing of peak harvest seasons and regional production trends could help farmers and traders make more informed decisions regarding chili cultivation and market strategies, ultimately leading to better price forecasts and more efficient supply chain management.

Furthermore, the ability of GBM to handle complex, non-linear relationships in the data demonstrates its strength in modeling agricultural price data, where traditional linear models may fall short. The model's accuracy and high AUC score indicate that it is a viable tool for real-world applications, providing stakeholders with actionable predictions that can be used to optimize pricing strategies, manage risks, and reduce uncertainty in the chili market.

Despite these promising results, the research acknowledges certain limitations. One limitation is the reliance on historical data, which may not fully account for unexpected market shifts or extreme events such as crop failures due to unforeseen weather conditions or global supply chain disruptions. The model may also benefit from the inclusion of additional data sources, such as international chili trade information or real-time market prices, to further enhance its predictive capabilities. Additionally, the dataset used in this study was limited to chili pricing information from specific regions and markets, and expanding the scope to include more diverse locations could improve the generalizability of the model.

4. Conclusion

In conclusion, this study successfully demonstrates the applicability of Gradient Boosting Machines (GBM) in enhancing the classification and prediction of chili prices. By utilizing a comprehensive dataset that incorporates various factors such as chili type, region, harvest season, weather conditions, and supply-demand dynamics, the GBM model was able to achieve a high level of accuracy and precision in classifying chili prices into distinct categories. The model's strong performance, with an accuracy rate of approximately 87% and an AUC score of 0.91, highlights its ability to capture complex, non-linear relationships in agricultural price data that other traditional models, such as Decision Trees and Random Forests, struggled to address. The feature importance analysis further revealed that harvest season and region were the most influential factors in determining chili price variations, confirming the significant role of seasonal and regional dynamics in agricultural pricing.

The findings of this research provide valuable insights for various stakeholders in the chili supply chain, including farmers, traders, and policymakers, by offering a more accurate and reliable method for price forecasting. The ability to predict price fluctuations based on seasonal patterns and regional differences can help stakeholders make better-informed decisions, optimize supply chain strategies, and reduce market uncertainties. Although the model demonstrated strong predictive capabilities, future research could benefit from the inclusion of additional data sources and advanced machine learning techniques, such as time-series analysis or models like XGBoost, to further refine and enhance price predictions. Overall, this study underscores the potential of machine learning approaches, particularly GBM, to improve decision-making processes and drive efficiency in agricultural markets, paving the way for more informed and data-driven strategies in managing commodity prices.

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5. Suggestion

Based on the findings of this study, it is suggested that future research should expand the scope of data collection to include a broader range of geographical locations, as well as additional market variables that may influence chili prices. Incorporating international trade data, transportation costs, and government policies related to agricultural subsidies could provide a more comprehensive view of the factors affecting chili prices. By extending the dataset to include a greater variety of regions and climates, the model could become more generalized and capable of making accurate predictions across different contexts, ultimately benefiting a larger set of stakeholders in the chili supply chain. Furthermore, integrating real-time market data could allow the model to adapt to short-term fluctuations and provide more immediate and actionable insights for decision-making in dynamic market environments.

In addition, future studies should explore the integration of more advanced machine learning techniques, such as XGBoost or LightGBM, which offer more efficient and faster algorithms compared to traditional GBM. These methods could improve the model's scalability, especially when dealing with large datasets and complex relationships between features. Time-series analysis, particularly with models like Long Short-Term Memory (LSTM) networks, could also be employed to forecast chili prices over extended periods, taking into account long-term trends and cyclical variations. Combining these advanced techniques with the existing dataset could enhance the predictive power of the model, making it an even more valuable tool for stakeholders looking to forecast and manage chili prices in the face of uncertainty.

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