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The Analysis of Crop Production Data for Predicting Future Trends of Highland Vegetables in Benguet

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Abstract. This study employs machine learning techniques to enhance agricultural prediction to secure future food supplies and support sustainable practices. It aims to forecast trends in highland vegetable crops in Benguet, providing invaluable insights for enhancing yields and contributing to vital food security initiatives. Notably, the researchers concentrated on crop production data due to inconsistencies and incompleteness in the historical datasets collated. Furthermore, it proposes a mobile platform for data collection from farmers, capturing their production and farming practices. This method intends to streamline the data collection process, enabling LGUs to collate and utilize the information effectively. The methodology employed a structured approach, encompassing data collection, preparation, analysis, modeling, and evaluation using Python programming and Power BI tools. In the analytical phase, a variety of machine learning models were explored, including Linear Regression, Lasso Regression, Ridge Regression, Decision Trees, SVM, and Random Forest. Model evaluation was based on the R^2, MAE, MSE, and RMSE. The Random Forest model emerged as the most suitable choice, boasting the best metrics for production purposes with an R^2 of 99%. The outcomes of this study hold significant potential, not only in reshaping agricultural practices and decision-making but also in fostering sustainable approaches to highland vegetable cultivation.

Keywords: Data mining; Machine learning; Predictive analytics; Sustainable agriculture; Crop production.

1.0 Introduction

Agriculture remains a cornerstone of many national economies, particularly in regions where it serves as a primary source of livelihood and food security. In the Philippines, the province of Benguet—often referred to as the "Salad Bowl of the Philippines"—is a leading producer of highland vegetables, contributing significantly to both local and national food systems (Quitaleg & Dumlao, 2023; FAO, 2021; Lopez-Ridaura et al., 2019). The region's agricultural productivity is vital not only for economic stability but also for ensuring food availability across the country.

Recent advancements in data science have introduced predictive analytics as a powerful tool in agriculture. Predictive analytics, which combines statistical techniques, machine learning, and data mining, enables the analysis of historical and real-time data to forecast future trends (Kumar & Malik, 2018; Liakos et al., 2018). In agriculture, this approach has been used to optimize crop yields, manage resources, and mitigate risks associated

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with climate variability and market fluctuations. Studies such as those by Gupta & Malik (n.d.) and Colombo-Mendoza et al. (2022) have demonstrated the efficacy of machine learning in identifying patterns within complex agricultural datasets, thereby supporting more informed decision-making.

Building on this foundation, recent research has further explored how advanced machine learning models can enhance the precision and responsiveness of agricultural forecasting systems. Araujo et al. (2023) highlight how predictive analytics, when combined with real-time data and AI-driven models, can significantly enhance decision-making in crop management and yield forecasting. Despite these technological advancements, Benguet's agricultural sector continues to face challenges. Data collection remains manual, mainly fragmented, leading to inconsistencies in historical records and limiting the accuracy of crop production forecasts. This gap in reliable, data-driven insights hampers the ability of farmers, policymakers, and local government units (LGUs) to plan effectively, often resulting in overproduction, shortages, and economic losses.

To address this gap, the present study aims to develop a machine learning-based predictive model for forecasting highland vegetable production in Benguet. The model will utilize historical data from LGUs, the Department of Agriculture (DA), and farmers' records. Additionally, the study proposes the development of a mobile-based data collection platform to standardize and streamline the recording of agricultural data. This dual approach seeks to enhance the accuracy and accessibility of production data, thereby supporting more effective agricultural planning and decision-making.

The significance of this study lies in its alignment with Republic Act No. 11293, the Philippine Innovation Act, which promotes the adoption of innovative and sustainable solutions across sectors, including agriculture (Republic of the Philippines, 2019). By integrating machine learning into agricultural forecasting, the study contributes to the modernization of farming practices in Benguet, fostering resilience and sustainability in the face of environmental and economic challenges. Moreover, this study aligns with several United Nations Sustainable Development Goals (SDGs), specifically Goal 9, which promotes innovation and resilient infrastructure; Goal 11, which focuses on building sustainable and inclusive communities; and Goal 12, which advocates for responsible production and consumption practices. By integrating data-driven solutions into agriculture, the research contributes to these global objectives through enhanced efficiency, reduced waste, and improved community resilience.

2.0 Methodology

2.1 Research Design

This study applies a data-driven quantitative framework design, integrating descriptive and predictive analytics to analyze historical crop production data and forecast future trends in Benguet's highland vegetable industry. Using machine learning techniques, it identifies key patterns affecting vegetable yields through a longitudinal approach, capturing seasonal variations over multiple years. Data is sourced from local government units (LGUs), the Department of Agriculture (DA), and farmers to ensure accuracy and comprehensiveness. A mobile platform will also be proposed to enhance real-time data collection and accessibility.

2.2 Research Methods

This study employs data mining techniques to analyze historical crop production data, ensuring accurate forecasting of highland vegetable yields in Benguet. The process follows key data mining stages, including data collection from various sources (LGUs, DA, and farmers), data analysis through preprocessing techniques like cleaning and normalization, and data modeling using algorithms in machine learning, including Random Forest, Decision Trees, and Regression models to identify key patterns and trends. Model evaluation is conducted to assess predictive performance and ensure accuracy. Additionally, Power BI is utilized for data visualization, converting raw data into interactive dashboards for informed decision-making. These procedures enable a comprehensive, data-driven approach to agricultural forecasting.

The study area includes the various topographies of the Philippine province of Benguet, which is part of the Cordillera Administrative Region. There are thirteen (13) municipalities in this area, each with distinctive topographical, climatic, and agricultural characteristics. The study's core comprises these municipalities, which provide essential data sources for analyzing crop trends and forecasting future agricultural results using machine-learning techniques. Figure 1 displays the study area's map, highlighting the geographical distribution of the 13

municipalities in Benguet: Atok, Bakun, Bokod, Buguias, Itogon, Kabayan, Kapangan, Kibungan, La Trinidad, Mankayan, Sablan, Tuba, and Tublay.

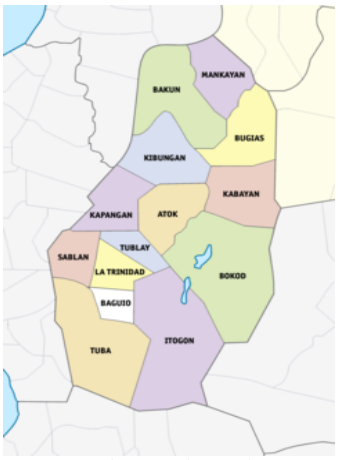

Figure 1. *Map of Benguet Province Showing the Study Area and Key Agricultural Zones*

Whereas the dataset used in this study comprises essential variables that play a crucial role in predicting crop yields in Benguet. These variables have been carefully curated and collected to capture key aspects of agricultural practices and climatic conditions. Table 1 shows a brief description of the main variables in the dataset, highlighting their names, data types, and units of measurement.

Table 1. *Dataset Attributes for Crop Yield Prediction*

Feature	Data Type	Description
Municipality	Categorical	Name of the municipality within the province of Benguet
Farm Type	Categorical	Type of farm, categorizing agricultural practices.
Year	Numerical	The year when the crop production data was recorded.
Month	Categorical	The month when the crop production data was recorded.
Crop	Categorical	Name of the high-value crop being cultivated.
Area Planted	Numerical	The total area of land where the crop was planted. Hectares (ha)
Area Harvested	Numerical	The total area of land where the crop was harvested. Hectares (ha)
Production	Numerical	The total crop production quantity. Metric Tons (mt)
Productivity	Numerical	The crop productivity, indicating the yield per unit area of land Yield per unit area (mt/ha)

2.3 Data Gathering Procedures

In the context of this study, data mining serves as the foundation for unraveling the complexities of crop trends and yields in the highland vegetable farms of Benguet. This section outlines the comprehensive steps taken to collect, prepare, analyze, and model the agricultural datasets used in the study (GeeksforGeeks, 2023).

Data collection involved a combination of in-person and virtual interviews, conducted in collaboration with the Office of the Provincial Agriculturist (OPAG) and the Department of Agriculture (DA). Initially, the consolidated datasets presented limitations due to the limited number of instances available for analysis. To enhance the predictive power of the models, the researchers requested data monthly, which improved granularity and aligned better with seasonal crop patterns. Although this approach expanded the scope of the study, it also introduced challenges such as data inconsistencies and variations in crop types. To address these, rigorous data verification procedures were implemented to confirm the reliability and exactness or correctness of the dataset.

Data preparation encompassed several key steps, including data cleaning, preprocessing, and correlation analysis. The raw data, sourced from multiple workbooks and worksheets representing various years, municipalities, and farm types in Benguet, was refined to focus on the top 10 high-value vegetable crops in the region. To handle inconsistencies, missing values, and outliers, preprocessing techniques such as normalization and feature scaling were applied, ensuring consistency and comparability across data attributes" (Cabello-Solorzano et al., 2023). The

dataset was also categorized by farm type—specifically "irrigated" and "rain-fed"—to provide deeper insights into how different agricultural practices influence crop production and yield.

To enhance the predictive accuracy of the model, correlation analysis was conducted to highlight the most dominant features and eliminate those with limited relevance. A Pearson correlation heatmap was utilized to visualize the strength and direction of relationships among variables, with correlation coefficients ranging from 0 (no linear relationship) to 1 (perfect positive correlation) (GeeksforGeeks, 2023a; de Melo Barros Junior et al., 2022). The analysis revealed a robust correlation of 0.97 between "Area Harvested" and "Production," suggesting that increased harvested area is closely associated with higher crop output. Additionally, "Area Planted" also demonstrated a moderate to strong correlation with "Production," with coefficients exceeding 0.5, supporting its inclusion in the predictive modeling process (Lopez-Ridaura et al., 2019).

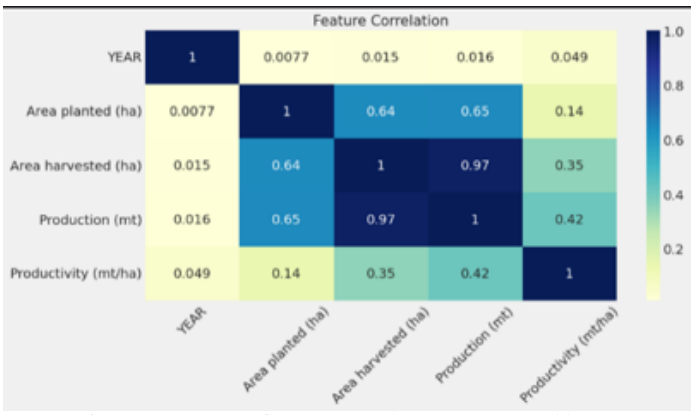

Figure 2. *Heatmap of Feature Correlations in Crop Yield Data*

After completing the dataset analysis, the researchers moved on to the modeling phase. The dataset was split into training and testing sets using an 80-20 ratio. According to de Bruin et al. (2021), this division is a widely accepted practice in machine learning, as it allows the model to learn from a substantial portion of the data while preserving a separate subset for unbiased evaluation. Figure 3 illustrates popular split ratios, emphasizing the efficacy of the 80-20 division for both training and model evaluation.

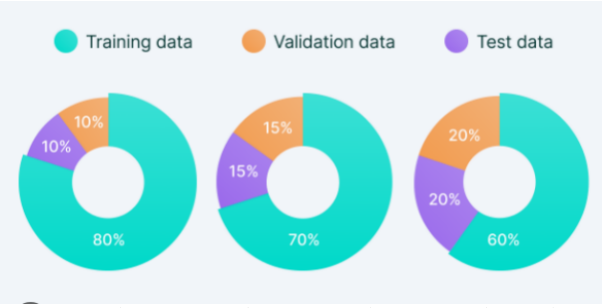

Figure 3. *Common Data Splitting Ratios showing typical train-test splits used in machine learning*

For model evaluation, the dataset was fed into the machine learning models and preprocessed to avoid overfitting. Pipelines were implemented for each model, incorporating standard scaling to enhance performance. After training, the models were evaluated using standard performance metrics such as R-squared (R^2) and various error measures (e.g., MAE, RMSE) to assess predictive accuracy and robustness.

2.4 Data Analysis Procedure

The study employed a quantitative research design to examine eight years of historical crop production data from Benguet. The dataset consisted of numerical variables, including crop yield, area harvested, and production volume. Six supervised machine learning algorithms—Linear Regression, Lasso Regression, Ridge Regression, Decision Tree Regressor, Support Vector Regression (SVR), and Random Forest Regressor—were applied to process and analyze the data. These algorithms were chosen for their capacity to model both linear and non-linear

relationships, as well as to address issues such as multicollinearity and feature selection. Each model was trained and evaluated using k-fold cross-validation, which helped ensure generalizability and minimized the risk of overfitting. Model performance was measured using standard evaluation metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2), providing objective assessments of predictive accuracy and robustness.

Validity was established by carefully selecting features relevant to crop yield prediction, thereby supporting construct validity, and by comparing model outputs to actual yield values, which addressed criterion validity. Reliability was demonstrated through the consistent performance of models across multiple data folds, indicating that the results were stable and not unduly influenced by specific data partitions. Although qualitative data were not included, the study enhanced trustworthiness by transparently documenting data preprocessing steps, algorithm selection, and evaluation procedures. The use of open-source tools and reproducible methods further strengthened the credibility of the findings. Results were visualized with interpretable graphs and incorporated into a dynamic dashboard, enabling stakeholders to explore and validate the outputs. The study acknowledged limitations such as missing values and data inconsistencies. It is recommended that future research integrate additional data sources, such as climate and market data, to improve model accuracy and contextual relevance further.

2.5 Ethical Considerations

In this study, formal informed consent forms were not used. Instead, the researchers submitted official request letters to the Department of Agriculture (DA) and the Office of the Provincial Agriculturist (OPAG) in Benguet to obtain permission to conduct interviews and gather data from their staff and affiliated farmers. These letters clearly outlined the study's purpose, the nature of the data to be collected, and the intended use of the information. Upon receiving approval, the agencies assisted in coordinating with selected participants. Before each interview or data collection activity, the researchers provided a verbal explanation of the study's objectives, the procedures involved and emphasized that participation was entirely voluntary. Participants were informed that they had the right to decline answering any question or to withdraw from the study at any point, without facing any consequences. The expected duration of participation was approximately 45 minutes to 1 hour. All information shared by the participants was secured for private use and limited to academic purposes only. Although no signed consent forms were collected, verbal consent was obtained from each participant before the start of the interview or discussion. This approach was considered appropriate given the institutional approval and the cultural context of the study.

3.0 Results and Discussion

3.1 Crop Trends and Patterns

In this section, the researchers delve into the observed trends and patterns of crop production across 13 municipalities in Benguet. This analysis aims to provide a nuanced understanding of the region's agricultural landscape, offering critical insights that can inform future decision-making for farmers, policymakers, and other stakeholders. The visualizations (see Fig. 4) illustrate how each municipality contributes to the broader picture of farming in the area, highlighting the interplay of various factors that influence agricultural productivity.

Notably, the researchers observed periods of low to zero production in regions that had historically maintained consistent output. This finding is particularly significant given Benguet's role as a major producer of highland vegetable crops in the Philippines. Similar disruptions in agricultural output have been documented globally, especially in regions heavily reliant on smallholder farming systems (Lopez-Ridaura et al., 2019). A sharp decline in crop production was observed in the year 2020. This drop suggests that the COVID-19 pandemic had a substantial influence on farm productivity in the province.

Further analysis revealed that the months with consistently high yields were from June to September. These months align with the typical harvest season, coinciding with the summer and early fall periods. The graph illustrates crop production trends across eight years, from 2015 to 2022, revealing a distinct seasonal peak in farming activity. A consistent surge in production is observed from May through September, aligning with the region's primary harvest season. This seasonal peak reflects the optimal growing conditions during these months, likely influenced by favorable weather patterns and established agricultural cycles. Recognizing this trend is

crucial for aligning resource allocation, market planning, and policy interventions to support farmers during these high-yield periods.

Figure 4. *Crop Production Trends by Municipality in Benguet (2015–2022)*

3.2 Crop Production Predictions

In this section, the researchers explore the predictive models developed using various machine learning algorithms to forecast future trends in crop production. These models are intended to serve as robust decision-support tools for farmers, policymakers, and other stakeholders in Benguet's agricultural sector. The figures present the predictions generated by six different algorithms, visualized in scatterplots. In these plots, the actual production data is illustrated through a red broken line running diagonally across the graph. At the same time, the predicted values are shown as blue points positioned near or along this line.

Most of the predicted values closely align with the red line, indicating that the models performed well in estimating crop production. However, discrepancies become more apparent at higher production values, where some predictions deviate significantly from the actual values. These deviations are known as outliers. In particular, a few outliers show that the models underestimated large production values, suggesting that the trained models struggled to generalize in these cases. This limitation may be attributed to the scarcity of data representing high production scenarios. Similar challenges have been reported in agricultural machine learning studies, where model performance declines in underrepresented data ranges (Bali & Singla, 2022).

Additionally, the models primarily relied on two features—Area Planted and Area Harvested—which may not fully capture the complexity of factors influencing crop yields. Research by Colombo-Mendoza et al. (2022) emphasizes the importance of integrating additional variables such as weather, soil quality, and pest incidence to improve model accuracy in agricultural forecasting.

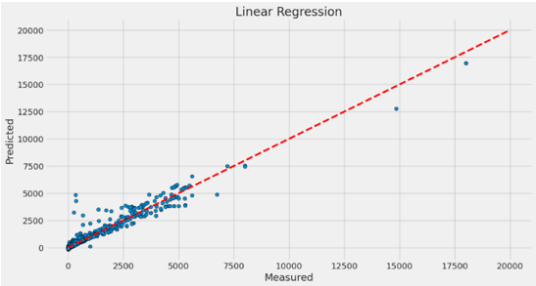

Figure 5. *Linear Regression Model Predictions for Crop Production*

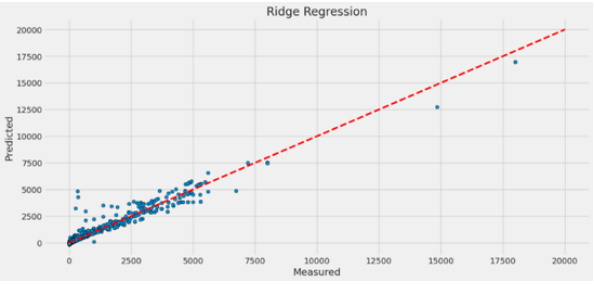

Figure 6. *Ridge Regression Model Predictions for Crop Production*

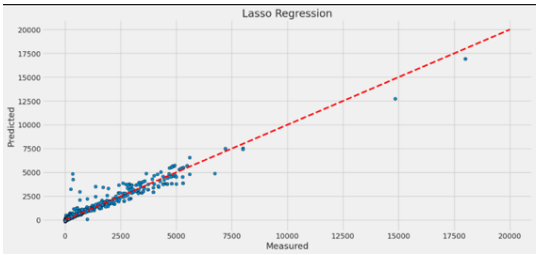

Figure 7. *Lasso Regression Model Predictions for Crop Production*

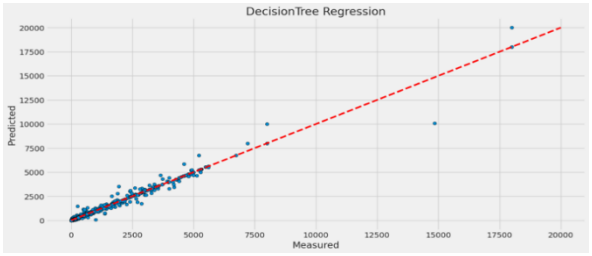

Figure 8. *Decision Tree Model Predictions for Crop Production*

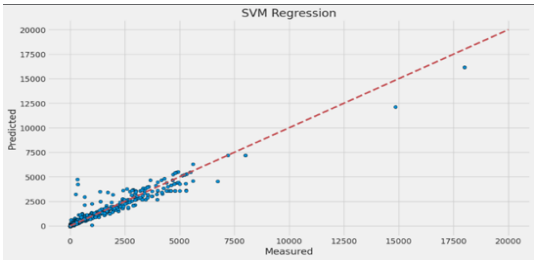

Figure 9. *SVM Regression Model Predictions for Crop Production*

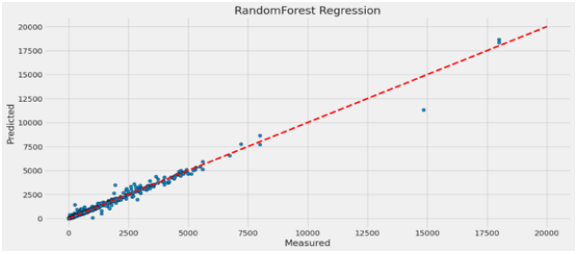

Figure 10. *Random Forest Regression Model Predictions for Crop Production*

The scatter plots presented in Figures 5 through 10 illustrate the performance of six different machine learning models in predicting crop production values. Specifically, Figure 5 shows results from Linear Regression, six from Ridge Regression, seven from Lasso Regression, eight from Decision Tree Regression, nine from Support Vector Machine (SVM) Regression, and 10 from Random Forest Regression. In each plot, the red dashed line represents the actual values, while the blue points denote the predicted values generated by the respective models. These visualizations highlight how closely each model's predictions align with the actual data. Ideally, the blue points should lie along the red dashed line, indicating perfect prediction accuracy. While the models generally perform well in estimating lower production values, deviations become more noticeable at higher values. These discrepancies, or outliers, suggest that the models struggle to maintain accuracy in predicting extreme or less frequent production levels, possibly due to limited training data in those ranges (Araújo et al., 2023).

3.3 Model Evaluation

After training the models, the researchers compared each using evaluation metrics commonly used for regression problems, such as the R-squared Score (R^2), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). These metrics allowed for a comprehensive assessment of the models' performance, enabling the researchers to identify the most effective model for predicting the target variable based on the input features.

Table 2. *Performance Metrics of Machine Learning Algorithms for Crop Production Prediction*

Models	R^2	Mean Absolute Error (MAE)	Mean Squared Error (MSE)	Root Mean Squared Error (RMSE)
Linear	0.96	66.83	24828.22	157.57
Lasso	0.96	66.83	24832.61	157.58
Ridge	0.96	65.40	24868.99	157.70
Decision Tree	0.98	16.15	12696.67	112.68
SVR	0.95	51.63	32740.11	180.94
Random Forest	0.99	13.51	7410.06	86.08

Table 2 presents clear evidence that the Random Forest algorithm outperforms the other models, achieving an R^2 value of 99%. This is notably higher than the 95–98% range attained by the alternative algorithms. Additionally, Random Forest records the lowest Root Mean Squared Error (RMSE) at 86.08, suggesting that the potential prediction error is approximately limited to 86 metric tons, significantly lower than the error margins of over 100 metric tons associated with the other models.

The use of ensemble learning techniques, particularly Gradient Boosting Regression, has been shown to enhance crop yield prediction accuracy in agricultural datasets significantly. Mishra et al. (2020) demonstrated that Gradient Boosting Regression effectively captures complex relationships in crop production data, offering robust performance across various agricultural scenarios. This aligns with the findings of the current study, where ensemble models such as Random Forest also exhibited superior predictive capabilities.

To better understand these results, it is important to examine the specific strengths of the Random Forest algorithm in agricultural modeling. Random Forest stands out for its strong performance across multiple evaluation metrics, making it well-suited for precise forecasting of future crop trends. Its ability to handle non-linear relationships and minimize overfitting is well-documented in agricultural machine learning applications (Jeong et al., 2016; Bali & Singla, 2022). Employing regression analysis and selecting appropriate models enhances our understanding of crop patterns and supports informed agricultural decision-making.

4.0 Conclusion

This research aimed to utilize machine learning algorithms to predict future crop yields in Benguet, using eight years of historical production data to support food sustainability efforts. A range of machine learning models was implemented, with the Random Forest algorithm demonstrating the highest predictive accuracy based on standard performance metrics. The results were presented through clear visualizations and integrated into a dynamic dashboard, facilitating broader dissemination and stakeholder engagement. While the study successfully met its objectives, it also identified limitations in data consistency and completeness, highlighting areas for future improvement. The findings of this study lay a foundational framework for enhancing agricultural forecasting in Benguet's highland vegetable industry. To build on this work, future research should focus on improving data integration, enhancing model accuracy, and developing real-time applications that can support decision-making for both policymakers and farmers.

Incorporating additional data sources, such as climate variables, market trends, and socio-economic indicators, can further enhance the resilience and profitability of farming systems. The integration of AI-driven decision support systems and Internet of Things (IoT) technologies for real-time monitoring can also advance precision agriculture practices. Moreover, the predictive framework developed in this study can be extended to other highland agricultural commodities beyond vegetable crops. Optimizing farm-to-market supply chains using predictive analytics can contribute to more efficient logistics and reduced post-harvest losses. Collectively, these advancements will support more innovative farming practices, strengthen climate resilience, and promote long-term food security in the region.

5.0 Contributions of Authors

Author 1: Conceptualization, Data Gathering, Data Preprocessing, Exploratory Data Analysis, Data Modeling, Model Evaluation, Visualization, Writing – Original Draft
Author 2: Supervision, Guidance in Data Gathering and Analysis

6.0 Funding

7.0 Conflict of Interests

The authors declare no conflict of interests.

8.0 Acknowledgment

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