

AI-ENABLED PREDICTIVE MODELING OF CROP QUALITY AND POST-HARVEST FOOD LOSS INTEGRATING AGRICULTURAL AND FOOD-QUALITY INDICATORS

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ABSTRACT

This study created and tested AI-based predictive models for food loss in the post-harvest chain, while combining agricultural, storage, handling and food quality indicators. A structured data set was used, with 1,200 observations and 29 variables for six crops and five geographical regions, where the main outcomes are crop-quality score, crop-quality class, post-harvest loss percentage and loss-risk class. Climatic conditions, soil moisture, nutrient inputs, harvest maturity, storage and transport characteristics, soluble solids, pH, firmness, color index and defect rate were all used as agricultural, post-harvest and food-quality predictors. Linear Regression, Decision Tree, Random Forest, XGBoost, Support Vector Machine, and K-Nearest Neighbors were tested using regression and classification metrics. It was revealed that agricultural condition score, colour index, harvest maturity and defect rate were significant variables influencing the quality of the produce while the storage temperature, soluble solids, pH, handling score, storage duration and defect rate were significant for post-harvest loss. Logistic Regression and SVM gave better-balanced classification results with R^2 values of 0.894 and 0.874 respectively, while Linear Regression gave R^2 values of 0.725 and 0.820 for crop quality and post-harvest loss respectively. The results highlight the usefulness of combining information related to agricultural production and food quality for prediction and post-harvest management based on data.

KEYWORDS: artificial intelligence; crop quality; post-harvest loss; machine learning; food-quality indicators.

1. INTRODUCTION

Post-harvest food loss and quality issues are significant for food security, agricultural production and sustainability of the food supply chain. The major problem faced by large quantities of agricultural produce is that they deteriorate either quantitatively or qualitatively from the time of harvesting until the time of consumption due to inappropriate handling, storage, transportation, environmental exposure and delayed marketing. These losses impact the economic returns farmers receive and on the availability of healthy food (Fao, 2018). Empirically, production conditions, post-harvest practices, market access, infrastructure and management are also factors that affect post-harvest losses (Debebe, 2022). There is a need for integrated approaches that take into account the conditions along the agricultural and post-harvest value chain to improve crop quality and minimise loss.

Agronomic, environmental, physiological and handling characteristics have to interact to affect the quality of crops. Product quality can be affected by various agricultural practices like soil management, nutrient management, climatic factors, irrigation, crop maturity, and harvesting practices, as well as the subsequent storage conditions. Precision agriculture technologies have the potential to measure these variables and help to manage agriculture more efficiently (SEPÚLVEDA et al., 2020). Studies based on machine learning have also shown that by taking into account the agronomic parameters, crop performance and the prediction of its yield significantly improved (Chlingaryan et al., 2018; Elavarasan et al., 2018). Appearance, defects, firmness, moisture, maturity and visual quality are all key characteristics post harvest which have an impact on marketability and deterioration. Visual features and hyperspectral methods have been used to identify fruit characteristics and fruit quality classes successfully by using machine vision and classification methods respectively (Ghazal et al., 2021; Han et al., 2021). Non-destructive techniques can also be used to detect defects in horticultural commodities without harming the products (Nturambirwe & Opara, 2020).

AI presents insights into the vast potential for capturing intricate relationships embedded in multi-dimensional agricultural and food-quality data. AI has the potential to reveal powerful insights into the complex relationships hidden within multi-dimensional datasets for agriculture and food quality. Machine learning can be used to combine climatic, production,

quality, and management data and parameters to enhance decision-making and provide better predictions (Ben Ayed & Hanana, 2021). The use of machines, such as regression, decision trees, random forests, support vector machines and deep learning, has been gaining popularity in agriculture (Benos et al., 2021). Deep learning also plays a role in automated pattern and image-based recognition in agriculture, which is more complex (Kamilaris & Prenafeta-Boldú, 2018). Automated food inspection, sorting, grading and quality evaluation are also enhanced with the use of computer vision and AI (Kakani et al., 2020). These can also be used to support farm risk assessment and prevention (Ghaffarian et al., 2022). Although there is an increasing use of AI in agriculture, studies on agricultural prediction and assessment of post-harvest quality are still conducted independently. There has been limited research that combines pre-harvest agricultural indicators with post-harvest handling conditions and food-quality indicators to predict both food loss and crop quality. Recent studies, therefore, highlight the importance of more robust AI tools particularly in post-harvest systems (Fadiji et al., 2023). Digital-twin and AI technologies are also showing great promise in the areas of integrated quality prediction, shelf-life management, and loss reduction (Jayavigneshwaran & Dishri, 2026).

In this study, the goal is to create predictive models using AI to integrate agricultural, storage, handling and food-quality indicators that predict food loss and quality in the post-harvest stage. In particular, it aims to find key factors that predict crop quality and loss, identify relationships between agricultural and quality factors, compare the performance of various machine learning-based models, and determine which factors are most influential in causing post-harvest losses.

2. MATERIALS AND METHODS

2.1 Dataset Description

A structured dataset was utilized that included 1,200 observations of 29 variables for agricultural conditions, post-harvest management, food-quality characteristics and crop-loss outcomes. The data included 6 crops (apple, banana, mango, potato, rice and tomato) and 5 regions. Crop_Quality_Score, Crop_Quality_Class, Post_Harvest_Loss_pct, and Loss_Risk_Class were the key predictive outputs. There were no missing values or duplicate records found. The dataset was analyzed as a structured agricultural dataset representing crop production, post-harvest management, food-quality characteristics, and crop-loss outcomes

2.2 Agricultural and Food-Quality Indicators

Agricultural predictors were field temperature, relative humidity, rainfall, soil moisture, nitrogen, phosphorus, potassium, harvest maturity, and agricultural condition score. Handling score, storage type, storage temperature, storage duration, transport type and transport duration were post-harvest indicators. The food quality parameters were soluble solids content, pH, firmness, color index and defect rate. Other post-harvest outcome variables that were available are estimated shelf life and marketability percentage.

2.3 Data Preprocessing and Exploratory Analysis

Data were checked for the absence of responses, duplicates, invalid data, and extreme values. Record_ID was not included as it was only used as an identifier. Quantitative variables were presented as mean, standard deviation, median, minimum and maximum and qualitative variables were presented in frequency counts and percentages. Categorical predictors were one-hot encoded and numerical predictors were scaled for use in scale-sensitive algorithms.

2.4 Feature Selection and Predictor Preparation

Ironically, in order not to suffer from target leakage, the predictor selection was conducted for crop-quality and post-harvest loss models separately. Alternative forms of the same outcome were not included in the outcome set for the corresponding predictor. Shelf life and marketability were also not included in primary predictive models, as they serve as downstream consequences of post-harvest loss. Influential predictors were identified by correlation analysis and by model-based feature importance and multicollinearity was checked prior to regression modeling.

2.5 AI and Machine Learning Models

Several machine-learning (ML) algorithms were tested to capture both linear and nonlinear relationships. The Regression models used were Linear Regression, Decision Tree Regression, Random Forest Regression, Extreme Gradient Boosting, Support Vector Regression, and K-Nearest Neighbors Regression. The classification models used were Logistic Regression, Decision Tree, Random Forest, Extreme Gradient Boosting, Support Vector Machine and KNN.

2.6 Model Training and Validation

80% of the data were used as the training set while 20% of the data were used as the testing set. Classification outcomes were obtained using stratified splitting to maintain class proportions. Within the training set, 5-fold cross-validation was performed and model hyperparameters were optimized by cross-validation. All the data were scaled and encoded only for the training set and applied to the test set to reduce information leakage.

2.7 Performance Evaluation Metrics

To assess the regression performance, R^2 , mean absolute error, mean squared error and root mean squared error were used. The accuracy, precision, recall, specificity, F1-score, ROC-AUC and confusion matrices were used to evaluate the classification performance. Macro-averaged metrics were used for imbalanced class outcomes, which cater to balanced evaluation across categories.

2.8 Statistical Analysis

A descriptive analysis and an inferential analysis were applied to explore the relationships between the agricultural conditions, the food-quality indicators, the crops quality, and the post-harvest loss. Pearson or Spearman correlation was used based on variable distribution and type of relationship. Analysis of variance or suitable non-parametric alternatives were used to analyze group differences across crop type, region, storage type and transport type. All selected predictors were subjected to multiple regression analysis and the effects found were statistically significant at $p < 0.05$.

3. RESULTS

3.1 Dataset Characteristics and Descriptive Statistics

The analysis comprised 1200 observations of 6 types of crops and 5 geographical regions. The data were indicative of a wide variety of agricultural, storage, handling and food quality conditions. The mean field temperature, mean field relative humidity, and the mean soil moisture were 25.02°C, 67.70%, and 28.35%, respectively. The average harvest maturity was 87.85% and the mean handling score was 6.94 on a 10-point scale. The mean crop-quality score was 74.50 while the average post-harvest loss was 30.42%. There was significant variation for storage duration, storage temperature, soluble solids, and post-harvest loss which were considered for subsequent predictive analysis. As illustrated in Table 1, the dataset contained sufficient variation in both predictor and outcome variables to support statistical and machine-learning analyses.

Table 1. Descriptive Statistics of Major Agricultural, Food-Quality, and Post-Harvest Variables

Variable	Mean	SD	Minimum	Maximum
Field temperature (°C)	25.02	4.96	10.00	38.00
Relative humidity (%)	67.70	11.84	35.00	95.00
Soil moisture (%)	28.35	6.88	10.00	48.00
Harvest maturity (%)	87.85	6.84	65.00	100.00
Handling score	6.94	1.64	1.00	10.00
Storage temperature (°C)	15.20	9.59	1.39	36.17
Storage duration (hours)	72.37	40.79	4.00	204.93
Soluble solids (°Brix)	10.64	6.22	1.00	21.91
Firmness (N)	14.73	3.70	5.89	28.29
Defect rate (%)	11.08	3.76	0.00	24.88
Agricultural condition score	8.18	1.11	4.38	10.00
Crop-quality score	74.50	6.13	51.22	94.28
Post-harvest loss (%)	30.42	6.96	9.54	50.48

3.2 Distribution of Crop Quality and Post-Harvest Loss Indicators

The Medium classification with 968 observations, High quality with 211 observations and Low quality with 21 observations accounted for the majority of the crop-quality classification. Risk of post-harvest loss had a different distribution with 627 cases being rated as High risk, 563 as Moderate risk and just 10 as Low risk. These distributions demonstrated the class imbalance, especially for the Low classes, which warranted the application of Stratified Splitting and Macro-Averaged performance measures when analyzing classification. Figure 1 shows the distribution of the observations in the Medium crop-quality class and in the Moderate-to-High post-harvest loss-risk classes.

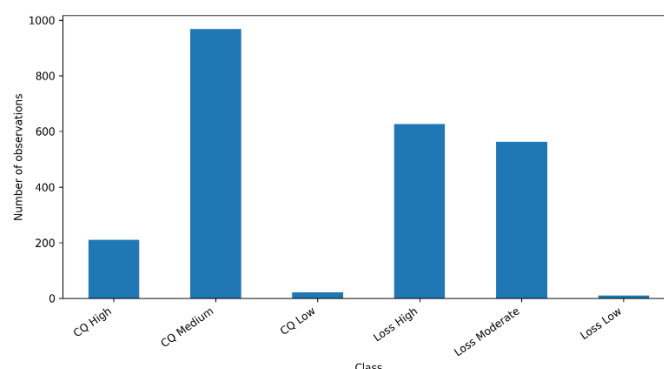


Figure 1. Distribution of Crop-Quality and Post-Harvest Loss-Risk Classes

3.3 Relationships Between Agricultural and Food-Quality Variables

Several statistically significant correlations were found between agricultural and food-quality indicators and the two continuous outcomes. Crop-quality score was positively associated with color index ($r = 0.532$, $p < 0.001$), agricultural condition score ($r = 0.519$, $p < 0.001$), and harvest maturity ($r = 0.425$, $p < 0.001$). Crop quality ($r = -0.264$, $p < 0.001$) was negatively associated with higher defect rate. The post-harvest loss exhibited the highest positive correlation with storage temperature (0.602, $p < 0.001$) and soluble solids (0.508, $p < 0.001$); while handling score and pH were negatively correlated with post-harvest loss. Table 2 demonstrates that crop quality was more strongly related to maturity, color, and

overall agricultural condition, whereas post-harvest loss was more strongly related to storage and food-quality characteristics.

Table 2. Correlations of Selected Predictors With Crop Quality and Post-Harvest Loss

Predictor	Crop Quality, r	p	Post-Harvest Loss, r	p
Harvest maturity	0.425	<0.001	-0.037	0.202
Handling score	0.046	0.110	-0.275	<0.001
Storage temperature	-0.089	0.002	0.602	<0.001
Storage duration	-0.053	0.065	0.167	<0.001
Soluble solids	-0.057	0.049	0.508	<0.001
pH	-0.206	<0.001	-0.400	<0.001
Firmness	0.020	0.482	-0.050	0.081
Color index	0.532	<0.001	0.007	0.820
Defect rate	-0.264	<0.001	0.245	<0.001
Agricultural condition score	0.519	<0.001	-0.135	<0.001

3.4 Important Predictors of Crop Quality

The random Forest permutation analysis revealed that the most influential predictor of crop-quality score was agricultural condition score, followed by color index. Other factors used in predicting the model include defect rate, harvest maturity, soluble solids and crop type. The predominance of agricultural condition score shows that a combination of the suitability of the production conditions was essential in the final quality determination, whereas the dominance of color index shows the significance of visible maturity and quality traits. Figure 2 shows that the agricultural condition score and color index yielded significantly larger reductions in predictive performance when permuted compared to the other variables, so these can be considered the key predictors of crop quality.

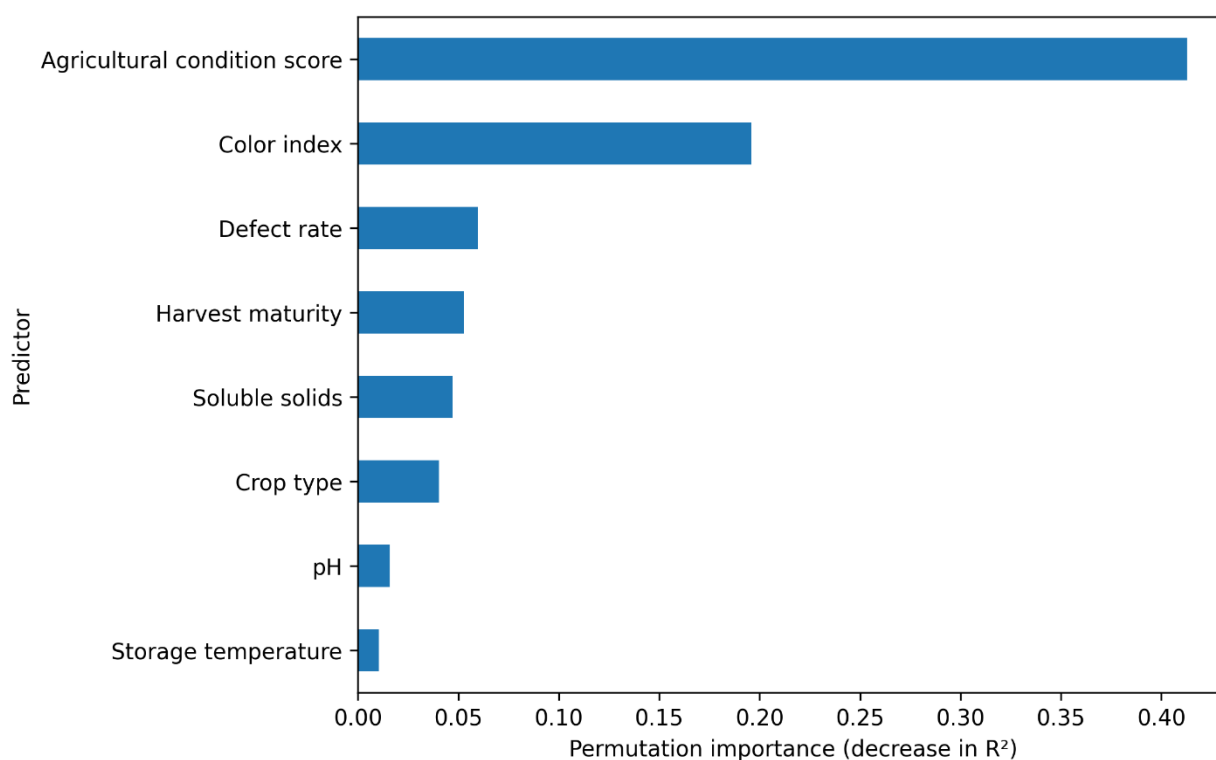


Figure 2. Permutation Importance of Major Predictors of Crop-Quality Score

3.5 Important Predictors of Post-Harvest Food Loss

Multiple regression analysis also enabled the independent effects of important predictors of post-harvest losses to be made clear. The primary positive standardized effects (β) were for storage temperature ($\beta = 0.582$, $p < 0.001$) and soluble solids ($\beta = 0.356$, $p < 0.001$). Higher handling scores significantly decreased predicted loss ($\beta = -0.247$, $p < 0.001$) and higher pH and agricultural condition scores were also significantly associated with lower losses. Expected loss increased with the use of longer storage periods and with higher defect rates. Crop-quality score was relatively modest when the other predictors were held constant. The model explained approximately 75.8% of the variance in post-harvest losses, and from the data presented in Table 3 it is seen that the variables that affected the post-harvest losses the most were storage temperature, soluble solids, handling quality and storage duration.

Table 3. Standardized Multiple Regression Predictors of Post-Harvest Loss

Predictor	Standardized β	p
Storage temperature	0.582	<0.001
Soluble solids	0.356	<0.001
Handling score	-0.247	<0.001
pH	-0.184	<0.001
Storage duration	0.160	<0.001
Agricultural condition score	-0.149	<0.001
Defect rate	0.131	<0.001
Crop-quality score	-0.034	0.071

3.6 Performance of AI-Based Prediction Models

The regression models demonstrated significant predictive power for crop-quality score and percentage loss after harvest. Linear Regression gave the lowest RMSE of 3.073 in predicting crop quality and 3.014 in predicting post-harvest loss. XGBoost also had good performance and had RMSE of 3.375 and 3.289 respectively. Random Forest and Support Vector Regression yielded intermediate results, and the Decision Tree yielded the biggest errors in prediction for both results. Figure 3 indicates that the Linear Regression and XGBoost models reported lower prediction errors with both results, and the single Decision Tree reported a relatively poor generalization.

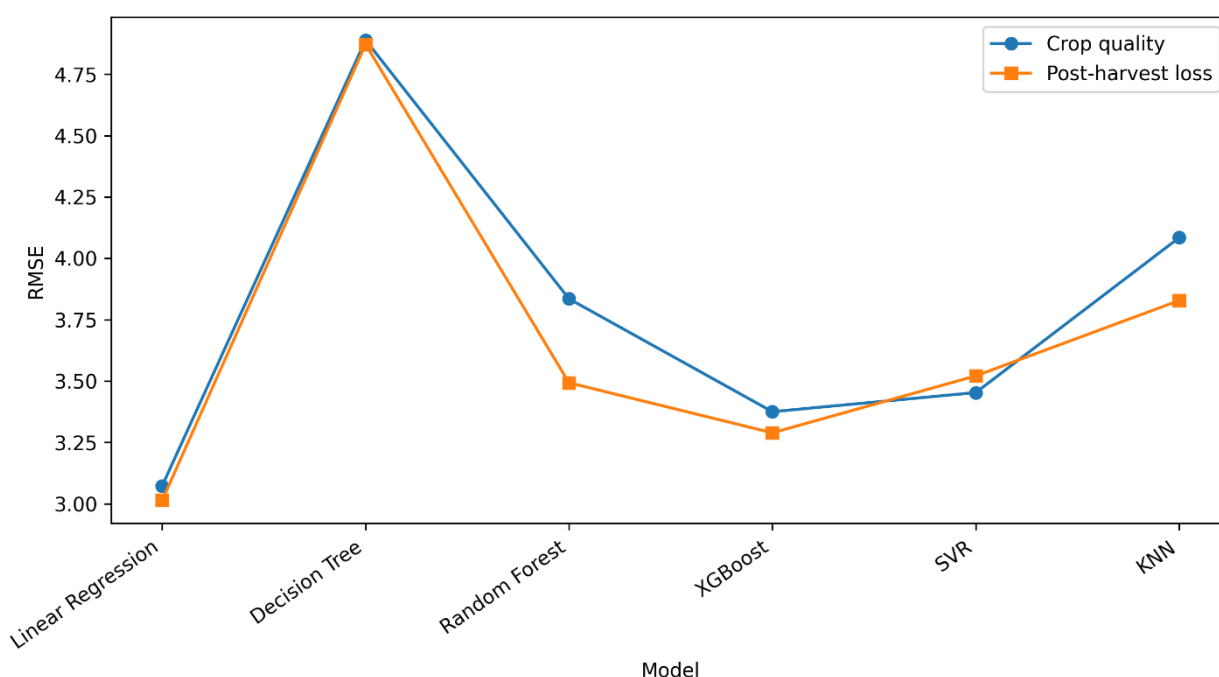


Figure 3. RMSE Comparison of Regression Models for Crop Quality and Post-Harvest Loss

3.7 Comparison of Machine Learning Models

Model comparison also revealed that the Linear Regression model predicted 72.5% of the variation in the test set of the crop-quality score and 82.0% of the variation in the post-harvest loss. The R^2 values obtained for XGBoost were 0.668 and 0.785 respectively. Logistic Regression showed the highest macro-F1 score for crop-quality class (0.752), and SVM showed the highest score for loss-risk classification (0.713) in classification analysis. The ROC-AUC values were generally high for the models with better classification abilities, achieving a value of 0.949 for loss-risk classification in the case of XGBoost. For the imbalanced classification problems, the performance of the regression-based baseline was good for continuous outcomes, and the Logistic Regression and SVM algorithms were more balanced, as shown in Table 4.

Table 4. Comparative Performance of Regression and Classification Models

Model	Crop Quality R^2	Loss R^2	Crop Quality Macro-F1	Loss Macro-F1	Crop Quality ROC-AUC	Loss ROC-AUC
Linear/Logistic Regression	0.725	0.820	0.752	0.688	0.929	0.946
Decision Tree	0.303	0.529	0.463	0.608	0.670	0.768
Random Forest	0.571	0.758	0.527	0.555	0.902	0.947
XGBoost	0.668	0.785	0.539	0.549	0.912	0.949
SVM/SVR	0.652	0.754	0.535	0.713	0.890	0.938
KNN	0.513	0.709	0.467	0.561	0.787	0.928

3.8 Feature Importance and Model Interpretation

The importance of the features was identified and it was found that the factors contributing to post-harvest food loss were different from the ones that were strongly associated with crop quality. The Random Forest permutation importance of the variables in the model for post-harvest loss was storage temperature, soluble solids, pH and handling score. Prediction was also done by defect rate, storage type, crop-quality score and storage duration. The results suggest that the post-harvest environment and handling conditions were more significant for loss prediction than many of the field-level variables. Handling quality, defect rate, pH, and storage conditions provided additional information in predicting post-harvest losses as shown in Figure 4 with storage temperature and soluble solids being the dominant predictors.

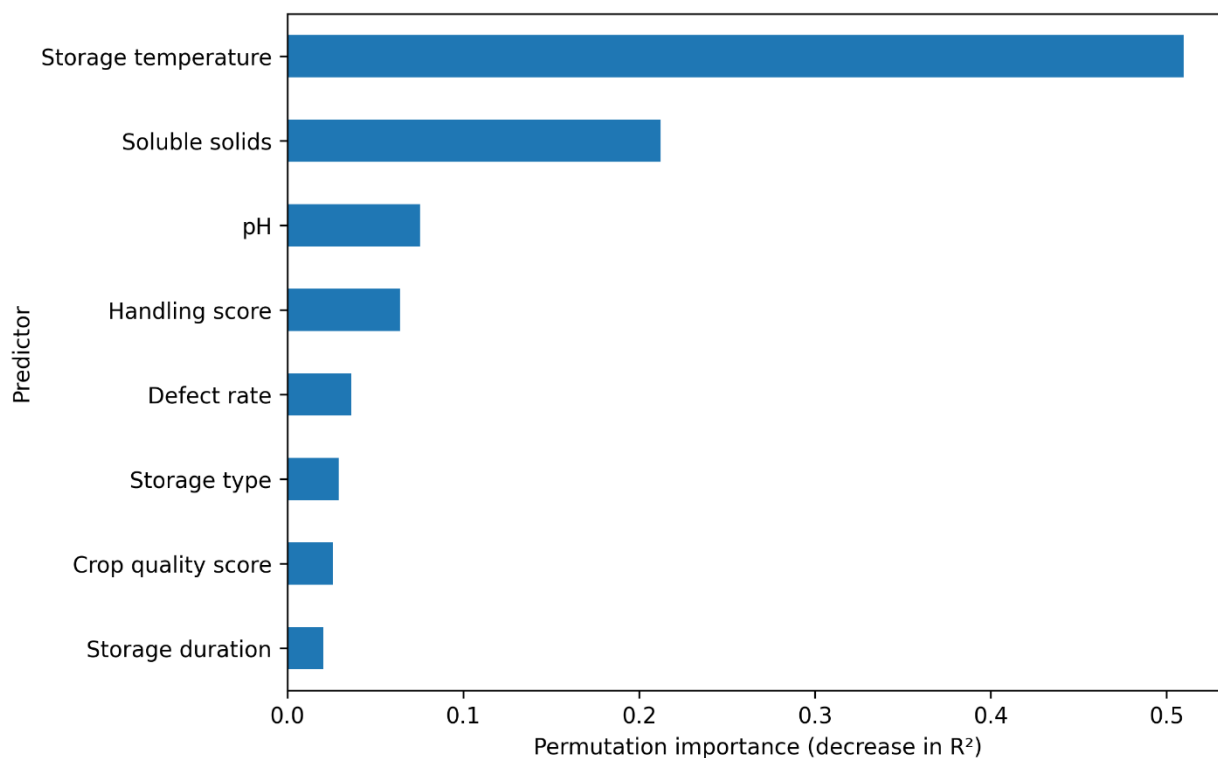


Figure 4. Permutation Importance of Major Predictors of Post-Harvest Food Loss

Overall, the findings support an integrated predictive approach in which agricultural conditions primarily influence crop quality, whereas storage, handling, and food-quality indicators become particularly important in determining post-harvest loss.

4. DISCUSSION

The results show that there are different, but related sets of agricultural and food-quality indicators that affect crop quality and post-harvest food loss. Agricultural condition score and the color index were most strongly correlated to crop-quality score, while storage temperature, soluble solids, pH, handling score, storage duration and defect rate were most strongly correlated to post-harvest loss. The high prediction accuracy achieved through various machine-learning methods is encouraging the use of AI in agricultural monitoring and decision-making (Liakos et al., 2018). In a similar study, it has been demonstrated that AI can combine diverse agricultural data to aid in the estimation of crop damage and management strategies focused on quality (Kundu et al., 2022).

Field management also affects crop condition at harvest, with agricultural condition score and harvest maturity being important factors affecting the quality of the crop. Environmental factors, nutrient availability, water management, and production systems affect crop performance. Artificial intelligence has increasingly started to be used to optimize these agricultural inputs and improve the efficiency of the use of these resources (Talaviya et al., 2020). The impact of color index on this also shows that visible maturity traits can be useful for estimates of crop quality and market readiness. AI technology is also used for fruit sizing and quality evaluation, which uses measurable morphological and visual traits to aid objective grading (Miranda et al., 2023).

Storage temperature was the most significant factor and the most important predictor of post-harvest losses, followed by soluble solids, pH, handling score, storage time and defect rate. The results stress the need for post-harvesting environmental control. Modern sensors, IoT, AI systems can continuously monitor stored agricultural commodities and detect conditions of quality deterioration (Lutz & Coradi, 2022). Additionally, hyperspectral and imaging technologies also record the chemical and physical quality attributes that are hard to assess with only visual evaluation (Lu et al., 2020; Wieme et al., 2022).

The predictive models gave satisfactory crop quality and post-harvest loss prediction. Linear Regression was very good at continuous outcomes and XGBoost was also competitive in its ability to predict. Logistic Regression and SVM showed better overall performance in classification for imbalanced categories. These results suggest that in relatively regular

relationships, complex algorithms are not superior to simpler ones. Matching algorithms with available data characteristics is also crucial for machine vision and AI-based post-harvest assessment (Tempelaere et al., 2023).

This outcome aligns with past studies, which have highlighted the importance of AI in quality assessment and post-harvest management. Imaging-based methods have been used to estimate fruit appearance, maturity stages, fruit defects, and fruit quality (Pathmanaban et al., 2019). The use of AI in date fruit harvesting and post-harvest operations has also shown promise for better sorting and quality evaluation, as well as increasing operational efficiency (Noutfia & Ropelewska, 2024). In a more general sense, digitalization and AI have been recognised as key enablers and instruments for sustainable food systems, through their ability to monitor, predict, track and optimize resources (Marvin et al., 2022).

The results indicated that to minimize post-harvest losses attention should be given to temperature control, careful handling, shorter storage periods, and early detection of defects. These indicators are incorporated into decision-support systems that monitor, in real time, storage and supply-chain operations powered by AI. This is especially important as food loss during primary production and post-harvest represents a significant inefficiency in global food systems (Parfitt et al., 2021). Measurements and identification of the key drivers of losses are therefore critical for targeted reduction measures (Spang et al., 2019).

The study was based on a structured analytical dataset covering multiple crops, agricultural conditions, post-harvest practices, and food-quality indicators. Consequently, the findings should be validated across independent agricultural populations, locations, seasons, and supply-chain settings before broad generalization. Therefore, the performance of the models cannot be directly transferred to individual crops, areas, or supply chains. Another possible reason for the class imbalance is that the classification performance has been affected by crop quality and risk of loss categories.

The predictive framework should be tested with multi-season multi-location field datasets in the future and should be updated with real-time sensor, imaging, and supply-chain data. The integration of AI with hyperspectral sensing, digital monitoring, and automated grading would enhance the ability to detect early signs of deterioration and aid in dynamic post-harvest management. These can positively influence the food-quality preservation and loss reduction value chains.

5. CONCLUSION

In this study, the authors showed that the integration of agricultural, storage, handling and food-quality indicators was used to jointly evaluate the quality of the crop and post-harvest food loss, with the help of AI-enabled predictive modeling. The results indicated that the agricultural condition index was the major contributor to crop-quality variation among the crops, and the storage temperature was the most important factor affecting post-harvest losses among the crops. For continuous outcomes, the evaluated regression methods yielded relatively high predictive performance, with Linear Regression and XGBoost outperforming other models. For crop-quality and loss-risk categories, the evaluated regression methods yielded a more balanced classification performance, with Logistic Regression and Support Vector Machine outperforming the others. The results show that the rate of post-harvest deterioration is not due to a single factor but due to the effect of production conditions, the product characteristics, and the post-harvest management. At an applied level, the study emphasizes the need for cooler storage, better handling practices, effective management of food storage and early quality evaluation in order to minimize food loss and maintain the marketable quality of the crops. The proposed analytical approach also showcases the potential of machine-learning models to help with data-driven decision-making in agriculture and post-harvest systems. To support future research, these findings should be externally validated using independent multi-location and multi-season agricultural datasets incorporating sensor, imaging, and supply-chain information and combine data from sensors, imaging, and the supply chain to enhance predictive accuracy and practical application.

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