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Research on Mass Prediction of Maize Kernel Based on Machine Vision and Machine Learning Algorithm

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Abstract: The yield assessment process during maize harvesting is a necessary means to ensure farmers' economic benefits and stable agricultural production. Predicting the mass of maize kernels is an important condition for yield detection. This study proposes a maize kernel mass prediction model based on machine vision and machine learning algorithms to determine whether the kernels are broken. By extracting the geometric features of maize kernels, a phenotypic feature dataset of maize kernels was constructed. Subsequently, popular machine learning algorithms were used to establish regression models for maize kernel mass, achieving quantitative prediction of maize kernel mass. The results indicate that the PLSR (Partial Least Squares Regression) and RF (Random Forest) algorithms are suitable for constructing mass prediction models for broken and unbroken kernels, respectively. The models established by the two algorithms achieved R-values of 0.941 and 0.925, respectively. Field trial results show that there is a strong linear relationship between the predicted maize kernel mass using the constructed model and the actual kernel mass. Therefore, this method can serve as an accurate, objective, and efficient detection method for maize yield.

Keywords: maize kernels; combine; image processing; prediction model; machine learning

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1. Introduction

In the global agricultural sector, maize is an important food crop that plays a significant role in ensuring global food security and farmers' economic benefits [1–3]. With the continuous growth of the global population and increasing agricultural demands, improving crop yields has become an urgent issue to address [4–6]. In this context, maize yield prediction has become one of the focal points of agricultural research [7–9]. Traditional yield prediction methods often rely on manual sampling and statistical analysis, which are not only time-consuming and labor-intensive but also susceptible to subjective factors, leading to insufficient prediction accuracy [10,11]. Therefore, utilizing advanced technological means for predicting maize harvest yields is particularly important.

In recent years, the rapid development of machine vision technology has provided new solutions for agricultural production [12,13]. Through image processing and computer vision, it is possible to obtain the morphological characteristics of maize kernels in real-time, thus laying the foundation for accurate yield prediction [14]. Machine vision can

enhance the efficiency and accuracy of data collection, providing farmers with scientific data support [15]. The continuously evolving machine learning technologies, such as Convolutional Neural Networks (CNN) and Support Vector Machines (SVM), offer more flexible and efficient solutions for maize yield prediction [16–19]. The integration of these emerging technologies with traditional agricultural practices is expected to significantly improve the accuracy and reliability of yield predictions.

The weight of maize kernels is an important basis for detecting maize harvest yields, as real-time detection of kernel mass can accurately reflect the dynamic changes in yield during the mechanized harvesting process [20–23]. By using modern technologies, farmers can obtain real-time mass data of the kernels during harvesting [24,25]. Farmers can quickly adjust their operational strategies to optimize harvesting outcomes [26]. Therefore, real-time detection of maize kernel mass can enhance the precision of yield detection and promote improved agricultural production efficiency.

Scholars both domestically and internationally have conducted extensive research on kernel quality detection methods. The German company Claas collected kernel images inside the kernel tank by installing a color camera on top of the scraper conveyor [27,28]. They used convolutional neural network algorithms to assess the contamination and breakage conditions reflected in the images. In 2019, Gu et al. performed segmentation on rice images based on the HSV color model and combined it with the MSRCR method [29], achieving online detection of rice with an accuracy of about 85% for breakage detection, although the detection precision was not high. In 2020, Han et al. identified rice contamination and breakage based on an improved U-Net network [30], with an average relative error of 7.00% for contamination and 6.72% for breakage. However, the processing time for a single image was 5 s, which is not suitable for real-time applications. In 2021, Zhang Shuai et al. utilized a multi-threshold segmentation method for online detection of flowing grain contamination and breakage [31], achieving a relative error of 9.72% for contamination and 9.39% for breakage, with a detection cycle reduced to 2 s. However, there were high requirements for the parameters, such as white balance and color temperature, and the detection effectiveness varied for different varieties. In 2022, Wu et al. combined the Mask R-CNN algorithm with edge detection algorithms to complete the detection of contamination and breakage in rice and wheat [32], with relative errors of 6.34% and 7.28% for rice and wheat breakage detection, respectively, but real-time performance was difficult to guarantee. In 2023, Zhang et al. achieved online detection of rice contamination and breakage during the harvesting process based on an improved DeepLab network and YOLO network [33]. However, the redundancy in the contamination and breakage network led to a detection time of up to 1.5 s for a single image, and the algorithm's lack of judgment regarding harvesting conditions could cause distortion in contamination and breakage data. However, most studies focus on crops such as wheat and soybeans, with relatively few investigations on the online monitoring of maize breakage.

Addressing the issue of traditional corn yield prediction methods (manual statistics) being time-consuming, labor-intensive, and susceptible to subjective factors, which leads to insufficient prediction accuracy. This study employed machine vision and machine learning algorithms to detect corn kernel mass for yield prediction. By efficiently extracting features from corn kernel images and applying the data to machine learning models, they achieved an effective evaluation of corn kernel mass. The combined use of machine vision and machine learning algorithms to detect corn kernel mass significantly improves efficiency and accuracy, enabling the rapid processing of large amounts of data and eliminating human error. Compared to traditional manual statistical methods, this approach is more adaptable. The research results are not only significant for the precise prediction of corn

yield during mechanical harvesting but also provide valuable technical support for the future development of smart agriculture.

2. Materials and Methods

2.1. Preparation of Maize Kernel Samples

To enhance the accuracy of the detection model, maize kernel samples were classified into two sets: one for intact kernels and the other for broken kernels, and we performed feature extraction on characteristics such as the area, perimeter, and roundness of the kernels. The broken kernel set includes various types of damage, such as broken and cracked kernels. Moreover, kernel mass is an essential parameter for estimating maize yield. Accurately labeling the mass of each kernel is vital for creating a predictive model for kernel mass within the training dataset. In the experiments, an electronic balance (Leqi, Yixing, China, with a capacity of 600 g and a precision of 0.01 g) was employed to measure the mass of each maize kernel. This measurement was repeated three times to obtain an average mass. The results of this experiment lay the groundwork for developing a mapping model to predict the shape and mass of maize kernels.

2.2. Design of Kernel Image Acquisition System

The collection of kernel images is essential for extracting the phenotypic features of maize and constructing predictive models for kernel mass. Therefore, a phenotypic feature collection system for maize kernels has been designed. The image acquisition device comprises a CCD camera (DFK-33UX265, Imaging Source GmbH, Bremen, Germany), a lightbox (0.6 × 0.6 × 0.5 m), four strip light sources (YX-BL5718K-W, Yantai Yongxin Vision Technology Co., Ltd., Yantai, China) mounted on the sides of the lightbox, and a laptop, as shown in Figure 1. To capture complete images of the maize kernel population, the camera was set at a working distance of 0.5 m. To ensure clear images of the corn kernels, the camera needed to be calibrated before formal data collection. The camera was fixed on a stand, ensuring even illumination from the light source. A halcyon camera calibration panel (DFvision, Dongguan, China) was then placed in the shooting position. The calibration target was positioned at the nearest focusing distance, the focus was adjusted, and a calibration image was captured. The clarity was checked to confirm there was no distortion. Finally, the camera settings were recorded for future reference.

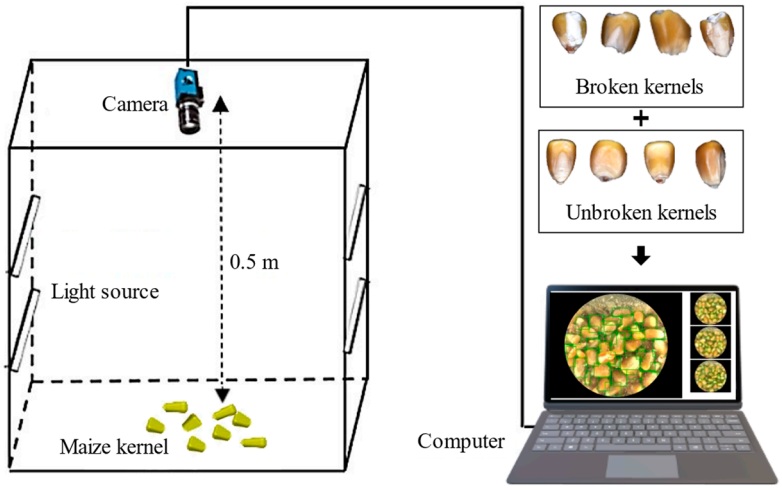


Figure 1. The working principle of maize broken kernel rate detection system.

2.3. Feature Extraction

The feature extraction of maize kernel images aims to extract two-dimensional characteristics that characterize the morphology of the maize kernels, including area, perimeter, area (S), perimeter (C), circularity (e) and the length of the minimum bounding rectangle (L). The area of a corn kernel refers to the total number of pixels it occupies in the image, obtained by counting the number of non-zero pixels. The perimeter refers to the total length of the boundary of the corn kernel, which can be calculated by measuring the edge pixels after edge detection. The roundness is defined as the ratio of the area of a corn kernel to the area of its minimum enclosing circle. The length of the bounding rectangle refers to the longest side of the smallest rectangle that encompasses the corn kernel, obtained by determining the maximum and minimum coordinates of the kernel (Figure 2). L is equal to the length of the minimum bounding rectangle (MBR) of the maize kernel ROI image. To enhance the convergence speed and accuracy of the model, the extracted features must be normalized using the following formula before being input into the model:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

where x' represents the normalized feature; $x_{\max}$ and $x_{\min}$ denote the maximum and minimum values of the feature parameters, respectively.

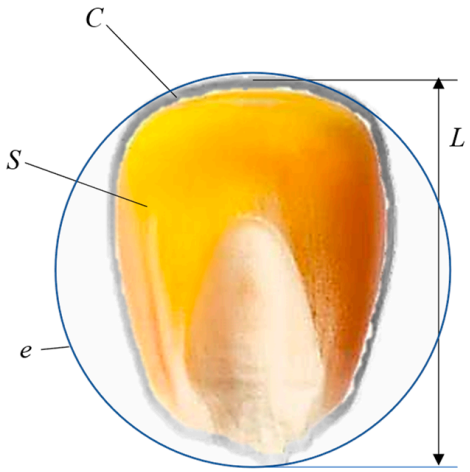


Figure 2. Maize kernel characteristic parameters.

The feature extraction of maize kernel images included several key steps. First, the images were read and preprocessed by converting them to grayscale, reducing noise, and binarizing them to enhance the clarity of the kernel boundaries. Next, image segmentation was performed through edge detection and contour finding to separate each kernel from the background. Subsequently, for each segmented kernel, features such as pixel area, perimeter, and the length of the minimum bounding rectangle were calculated to describe the kernel's morphology. These features were recorded in a data file for input into machine learning models, which effectively analyzed and quantified the morphological characteristics of maize kernels. The process of measuring multiple maize kernels within images involved preprocessing, segmentation, and feature extraction. Initially, the image underwent noise reduction and enhancement to ensure clear kernel boundaries. Then, techniques such as thresholding or edge detection were applied to separate each kernel from the background and other kernels. After segmenting the kernels, the feature extraction process was conducted for each segmented kernel to calculate their respective pixel area,

perimeter, and length of the minimum bounding rectangle. Finally, the extracted features were recorded for further analysis or input into the model.

After feature extraction and normalization, the maize kernel dataset comprises a total of 100 samples, with each sample consisting of three two-dimensional features and one mass label. A random selection of 75% of the dataset is used as the training set, while the remaining 25% is allocated as the test set.

2.4. Machine Learning Algorithm for Mass Prediction Model Construction

To enhance the accuracy of the maize kernel mass prediction model, this study employs both linear and non-linear machine learning algorithms to construct the mass prediction model. Linear algorithms assume a linear relationship between input features and output targets, making them simpler and faster to compute, with common examples including linear regression and logistic regression. They perform well when data exhibit linear characteristics but struggle with non-linear relationships and can be sensitive to outliers. In contrast, non-linear algorithms can capture complex patterns and relationships through more intricate mathematical functions, such as decision trees, random forests, and neural networks. While they offer increased predictive accuracy and can effectively handle data with non-linear characteristics, they tend to be more computationally intensive, prone to overfitting, and less interpretable. The choice between linear and non-linear algorithms depends on the specific nature of the data, the complexity of the problem, and the need for model interpretability. Specifically, four regression algorithms were utilized: Partial Least Squares Regression (PLSR), Random Forest (RF), Support Vector Regression (SVR), and K-Nearest Neighbors (KNN). The hyperparameter settings for each algorithm are as follows:

(1) PLSR

PLSR reduces the dimensionality of input features by extracting latent variables (principal components) that explain the strongest linear relationships between features and the target variable [34]. This solves multicollinearity while reducing redundancy. During regression, these components are fed into a linear model to predict output.

(2) RF

Random Forest employs the "Bootstrap" method to generate samples from the training set and build decision trees on each sample [35]. Each tree considers only a portion of the features when splitting nodes, increasing the diversity of the model and reducing variance. By aggregating multiple decision trees, Random Forest can significantly enhance predictive accuracy.

(3) SVR

The core idea of SVR is to maximize the margin while allowing some errors [36]. In a high-dimensional feature space, SVR maps data to a higher dimension using a kernel function to find the best hyperplane. By adjusting the regularization parameter C and epsilon, one can control the model's complexity and tolerance for error.

(4) KNN

The KNN algorithm operates by measuring the distances between samples (such as Euclidean distance or Manhattan distance) [37]. For classification problems, it predicts the class most common among the K nearest neighbors; for regression problems, it takes the average value of the K neighbors as the predicted result. The key to this algorithm lies in choosing an appropriate K-value and distance metric. A K-value that is too small may lead to overfitting, while one that is too large may cause underfitting.

Hyperparameter tuning plays a crucial role in the construction and optimization of machine learning models. They affect the model's performance, complexity, training efficiency, and its performance on new data. Therefore, the proper adjustment of hyperparameters is fundamental to building effective and reliable machine learning models. In this study, the initial setting of hyperparameters of each algorithm is shown in Table 1.

Table 1. The initial setting of each algorithm's hyperparameter.

Algorithm	Hyperparameter	Value Range
RF	Number of decision trees	50–200 (step size of 10)
	Maximum depth	1–91 (step size of 1)
	Maximum number of features	1–3
SVR	Kernel type	Linear, Polynomial, RBF, Sigmoid
	Regularization parameter C	0.1, 1, 10
	Gamma parameter	0.01, 0.1, 1
KNN	Number of neighbors (n_neighbors)	1–15 (step size of 1)
	Weights	'distance' or 'uniform'

2.5. Evaluation Metric

Model performance evaluation metrics are fundamental for measuring the accuracy and reliability of predictive models. In this study, three main evaluation metrics were employed: standard deviation (SD), root mean square error (RMSE), and correlation coefficient (r). Standard deviation (SD) measures the degree of variability between the model's predictions and the actual values; a smaller SD indicates that the model's predictions are more stable. Root mean square error (RMSE) quantifies the prediction error, reflecting the average deviation between predicted values and true values; lower RMSE suggests a stronger predictive capability of the model. Meanwhile, the correlation coefficient (r) indicates the extent to which the model explains the variability of the data, with R^2 values ranging from 0 to 1—higher values closer to 1 denote better model fit. These metrics provide a comprehensive quantitative basis for evaluating model performance, thus helping to assess the strengths and practicality of the model in real-world applications. The corresponding formulas are as follows [38]:

$$r = \sqrt{1 - \frac{\sum_{i=1}^{n} \left(y_{i,actual} - y_{i,predicted}\right)^2}{\sum_{i=1}^{n} \left(y_{i,actual} - y_{average}\right)^2}}$$

$$SD = \sqrt{\frac{1}{\mathrm{N}} \sum_{i=1}^{N} (x_i - \overline{x})^2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left(y_{i,actual} - y_{i,predicted}\right)^2}{N - 1}}$$

where $y_{i,actual}$ is the actual value of the i-th sample. $y_{i,predicted}$ is the predicted value of the i-th sample. $y_{average}$ is the average of the actual values. n is the total number of samples. N is the total number of samples. x_i is the value of the i-th sample (formula for standard deviation). $\overline{x}$ is the average value of the sample (formula for standard deviation).

3. Results

3.1. Correlation Analysis of Maize Kernel External Feature and Mass

In the comparative analysis shown in Figure 3, the relationship and strength of each feature with respect to mass are clearly visible. First, Figure 3a illustrates a strong positive

correlation between area and mass, with a correlation coefficient R reaching 0.8718. This indicates that as the area increases, the mass also significantly improves. In the samples, a larger surface area may accommodate more material, thus increasing mass. Therefore, area can be considered an important predictive variable for mass.

Figure 3b depicts the relationship between perimeter and mass. Although the correlation coefficient is 0.801, indicating a strong positive correlation between perimeter and mass, its strength is slightly inferior to that of area. This may be related to the complexity of shape in certain cases. While perimeter significantly impacts mass, its influence is somewhat reduced compared to the direct relationship with area, potentially due to the variability in the shapes of individual samples.

Figure 3c and Figure 3d address the influence of shape features. The results show that circularity and rectangularity have weaker relationships with mass, with coefficients of R= 0.2126 and R = 0.1952, respectively. The low correlation coefficients in these two charts suggest that while shape features can influence mass to some extent, their impact is much less pronounced than that of area and perimeter. This may imply that the kernel mass is more dependent on its volume or surface area.

Overall, area and perimeter are key predictive factors for mass, while circularity and rectangularity may have limited significance in understanding the variability of mass. The correlation analysis results between maize kernel characteristics and mass indicate a linear relationship between the external features of both broken and unbroken kernels and their mass. However, the linearity between these characteristics and grain mass could be enhanced. Consequently, a machine learning algorithm was employed to optimize multiple kernel features for more accurate prediction of kernel mass.

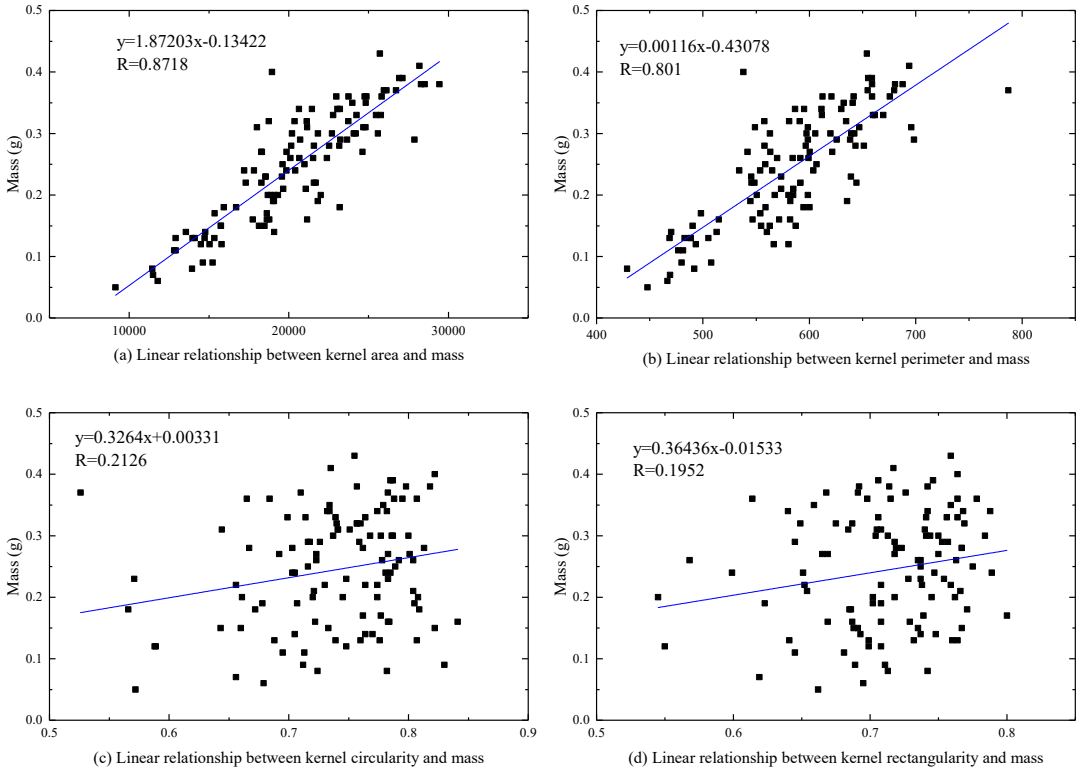


Figure 3. Correlation analysis between feature and mass for maize kernel.

3.2. Performances of Mass Estimation Models Based on Machine Learning Algorithm

3.2.1. Process of Kernel Quality Prediction Based on Machine Learning Algorithm

The structure and process of the maize kernel mass prediction model are illustrated in Figure 4. First, features related to the maize kernel characteristics ("S", "C", "e", "L") are

extracted and integrated for subsequent mass prediction. The model utilizes four machine learning algorithms, PLSR, RF, SVR, and KNN, to train and predict based on these features. Additionally, the model considers the impact of broken and unbroken kernels, ultimately outputting the corresponding maize kernel mass prediction to ensure the accuracy of crop assessment.

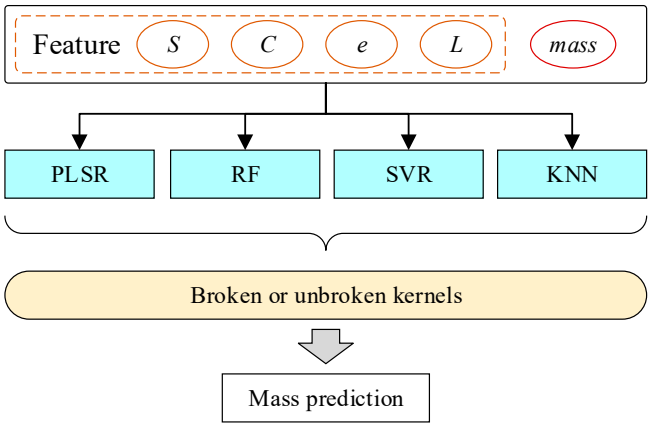


Figure 4. Prediction principle of kernel mass based on machine learning algorithms.

3.2.2. Determination of Optimal Algorithm for Prediction Model

The accuracy of mass prediction models for both broken and unbroken kernels is illustrated in Table 2 and Figure 5. The Taylor diagram provides a visual representation of these models built with various algorithms, allowing for an easy evaluation of their strengths and weaknesses. This diagram assesses model performance by comparing predictions against actual observations through standard deviation (SD), correlation coefficient (r), and root mean square error (RMSE). Key components of a Taylor diagram include the following:

Observation Point (Obs): the standard deviation and mean of the observed data. Radius: the magnitude of the standard deviation; larger distances from the model's center indicate higher standard deviations. Angle: the angle between the model marker and the horizontal line represents the correlation (r) with the reference data; a smaller angle indicates a stronger correlation. RMSE: the distance from the point to the horizontal axis; shorter distances signify lower RMSE, meaning the model's predictions are more accurate.

In a word, label points of the model (marked in red), radiation (marked in blue), horizontal (vertical) axis (marked in black), and dashed lines (marked in green) in the Taylor chart represent the model, correlation coefficient (r), standard deviation (SD), and root mean square error (RMSE), respectively (Figure 3).

Table 2. Precision comparison of different models.

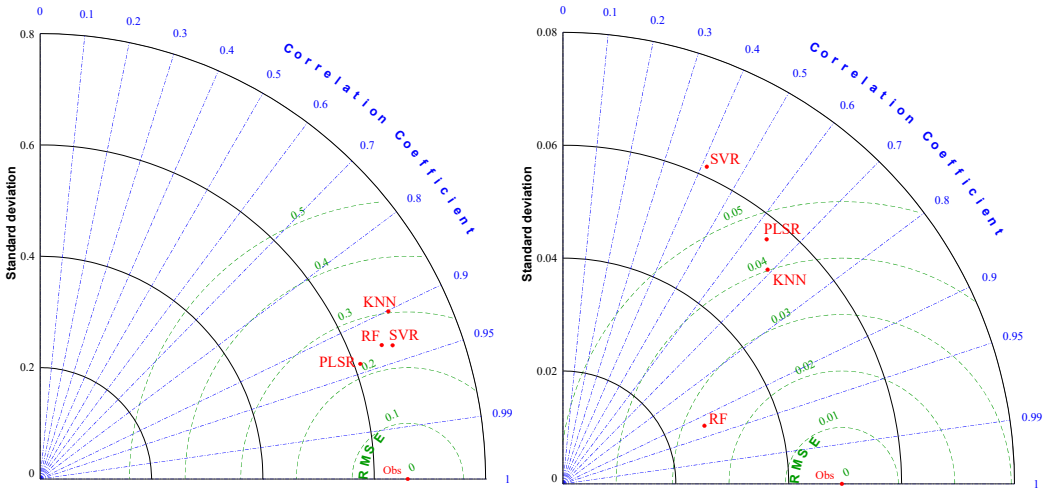
Model	Prediction of Broken Kernel Mass			Prediction of Unbroken Kernel Mass		
	r	SD	RMSE	r	SD	RMSE
PLSR	0.941	0.6111	0.2236	0.640	0.0564	0.1673
RF	0.931	0.659	0.2450	0.925	0.0271	0.1729
SVR	0.935	0.677	0.2416	0.413	0.0617	0.1811
KNN	0.901	0.694	0.3030	0.691	0.0525	0.1658

In comparing the performance of different models for predicting the mass of broken and unbroken kernels using the correlation coefficient (r), standard deviation (SD), and root mean square error (RMSE), we can conduct an in-depth evaluation.

For the prediction of broken kernel mass, the PLSR model exhibits the highest correlation coefficient r of 0.941, indicating strong predictive capability. Following closely are the SVR and RF models, with coefficients of 0.935 and 0.931, respectively. While these models also perform well, their predictive ability is slightly inferior to that of the PLSR model. The KNN model shows a lower r of just 0.901, reflecting relatively lower predictive accuracy. In terms of standard deviation and RMSE, the PLSR model has an SD of 0.6111 and an RMSE of 0.2236, indicating a small deviation between predicted and actual values, which demonstrates higher stability and accuracy. Comparatively, the RF model performs slightly better in these two aspects, although it does not surpass PLSR. The KNN model shows high values for both standard deviation and RMSE, indicating overall instability in its predictions.

When analyzing the prediction of unbroken maize kernel mass, the RF model stands out with the highest correlation coefficient r of 0.925, marking its superiority among all models in this task. The PLSR model, while slightly lower with an r of 0.640, excels in both standard deviation and RMSE, with values of SD = 0.0564 and RMSE = 0.1673, indicating high predictive accuracy. The SVR model has a lower r of 0.413, showing a relatively weak association and consequently poorer performance in SD and RMSE.

Overall, the PLSR model performs best in predicting the mass of broken kernels, while the RF model demonstrates the highest effectiveness in predicting the mass of unbroken maize kernels. If considering a comprehensive evaluation, PLSR is the better model choice, particularly for the prediction of broken kernel mass. In contrast, the RF model exhibits stronger predictive capability for unbroken kernel prediction. Some researchers have developed mass prediction models for corn kernels using deep learning algorithms. For instance, Zhang et al. implemented a convolutional neural network (CNN) for this purpose, achieving mass regression model r-values of 0.996 for broken kernels and 0.979 for unbroken kernels [39]. While the r-values from kernel mass regression models built with machine learning algorithms were slightly lower than those from deep learning methods, they still exceeded 0.9, meeting the anticipated standards. Additionally, machine learning algorithms generally require less training time and fewer resources compared to deep learning techniques. This efficiency enables the quicker development of mass prediction models for various popular maize varieties in China, where there are over 2000 registered corn varieties [40]. Given the need for rapid and effective modeling methods in the industry, machine learning algorithms may be more appropriate for constructing similar models while fulfilling the necessary performance criteria.



(**a**) Broken (**b**) Unbroken

Figure 5. Accuracy comparison of prediction models for broken and unbroken kernel mass.

3.2.3. Optimal Model Algorithm Comparison Analysis

The excellent performance of the PLSR model in predicting the mass of broken kernels is primarily due to its robust linear regression capability, which effectively captures the relationships between data features. Additionally, the mass of broken kernels is influenced by multiple factors, and PLSR integrates various variables through principal component analysis. This reduces multicollinearity and enhances predictive accuracy.

On the other hand, the outstanding performance of the RF model in predicting the mass of unbroken kernels can be attributed to its inherent ensemble learning mechanism. Random Forest constructs multiple decision trees and employs voting to effectively handle the non-linear characteristics of the data, exhibiting high robustness. This allows RF to adapt better to variations in samples when dealing with more complex features, thus improving prediction accuracy.

Regarding broken and unbroken kernels, the data features may exhibit different distribution characteristics. The mass of broken kernels may be associated with relatively consistent features, while the mass of unbroken kernels may display more complex patterns due to the diversity of factors such as shape and size. In such cases, the RF model can better capture these complexities (the differences among unbroken kernel features are smaller yet more intricate), leading to its advantage in predicting the mass of unbroken kernels.

In summary, the PLSR model performs best in predicting the mass of broken kernels due to its strong linear feature extraction capabilities. Conversely, the RF model has superior performance in predicting the mass of unbroken kernels, owing to its ability to handle complex, non-linear data. When selecting a model, it is essential to evaluate it based on the specific characteristics of the problem and data structure to achieve optimal predictive results.

3.2.4. Optimal Algorithm Tuning Process

To further elucidate the process of determining the optimal model, this manuscript analyzes the hyperparameter tuning process for selecting the best model (Figure 6). Taking the RF algorithm for predicting the mass of unbroken maize kernels as an example, we will examine the hyperparameter tuning process for the RF algorithm.

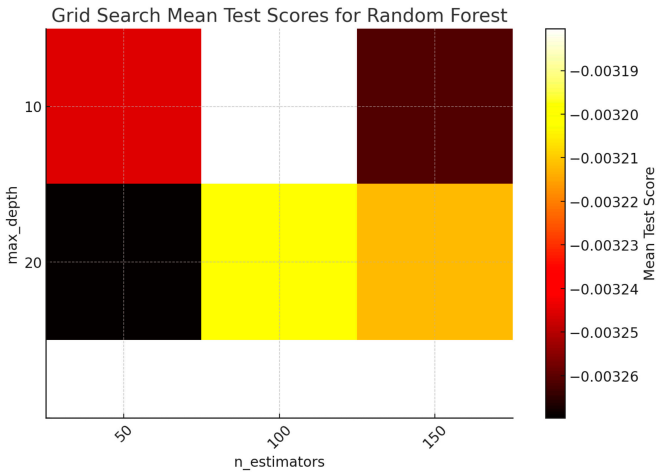


Figure 6. Optimization results of machine learning algorithm hyperparameters.

Figure 6 displays the mean test scores of the Random Forest model under different combinations of hyperparameters. The axes represent the maximum depth (max_depth) and the number of estimators (n_estimators), with color intensity indicating the average test scores of the model. It is first observed that when the maximum depth is set to 20

and the number of estimators is set to 100, the chart shows the optimal mean test score of approximately −0.00319, which is reflected in a distinct yellow color, indicating that this parameter combination yields the best predictive performance. In contrast, if max_depth is set to 10, regardless of whether n_estimators is set between 50 and 150, the model displays slower scores, suggesting inadequate capacity to capture data features.

Conversely, when max_depth is set to 30, it performs reasonably well; however, at lowern_estimators (such as 50), its performance remains unsatisfactory, indicating that the number of trees is insufficient to support effective predictions.

Moreover, although higher values of max_depth between 20 and 30 can achieve high scores, the number of n_estimators becomes particularly important. Especially when n_estimators is set to 100, the mean test scores overall outperform other configurations, regardless of the variation in max_depth. Additionally, as n estimators increases, the prominent hot zones in the visualization are confined to the area where max_depth is between 20 and 30, indicating that within this range, the number of trees significantly determines the model's predictive capability.

Therefore, through a comparison of the performances of different combinations, it can be concluded that the optimal hyperparameter combination is max_depth = 20 and n_estimators = 100. This combination ensures a good balance between model complexity and accuracy, enhancing the overall performance and predictive precision of the Random Forest in handling the data. Choosing appropriate hyperparameters is crucial for improving model performance, allowing us to better capture the intrinsic features of the data and ultimately achieve more reliable prediction results.

3.3. Field Trial Analysis

To validate the performance of the maize kernel mass prediction model, field trials were conducted. The constructed maize kernel mass prediction system was mounted on a Changfa CF806 combine harvester (Jialian, Changzhou, China). Specifically, the kernel mass detection system was located at the top of the corn combine harvester's kernel tank. During the operation of the corn combine harvester, the corn kernels accumulated in the kernel tank. Mass detection sensors could take real-time photos of the corn kernels entering the kernel tank. This allowed for real-time monitoring of the corn harvest yield. Image processing algorithms were used to process the collected kernel sample images to obtain corresponding feature data. Then, the obtained feature data were analyzed and used to predict the mass of the corn kernels through regression. Industrial cameras captured images of the kernel in real-time to facilitate yield prediction. Figure 7 illustrates the relationship between the actual values and the predicted values of maize kernel mass. The correlation coefficient R was 0.926, indicating a strong positive correlation between the two. The prediction model performed well in most cases, as the data points were closely clustered around the red regression line, suggesting that the predicted results were close to the actual values. However, there were some outliers as actual values approached 0.5 g, indicating potential room for improvement within this range. In summary, the results of the field trials indicated a significant linear relationship between the actual values of maize kernel mass and the predicted values from the model, demonstrating strong correlation. This suggested that the model possessed relatively high credibility when predicting maize kernel mass.

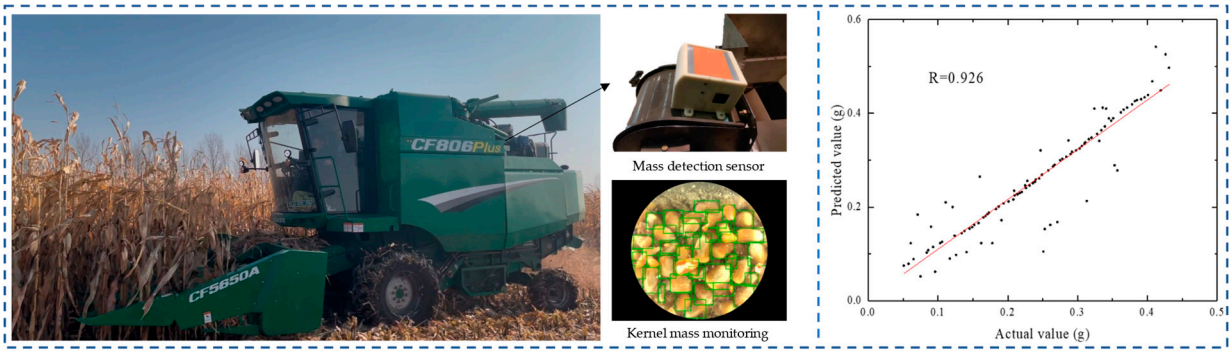


Figure 7. Predictive performance of maize breakage rate model.

4. Conclusions

This study developed a maize kernel mass prediction model based on machine vision and machine learning algorithms, enabling real-time detection of yield during the maize harvesting process. By extracting four geometric features of maize kernels (area, perimeter, circularity, and rectangularity), a regression model for maize kernel mass was constructed. Additionally, four machine learning algorithms were employed to optimize the model's accuracy, aiming for enhanced performance. The results indicate that the PLSR algorithm is better suited for predicting the mass of broken kernels, with correlation coefficient r, standard deviation (SD), and root mean square error (RMSE) values of 0.941, 0.6111, and 0.2236, respectively. The RF algorithm, on the other hand, is an ideal choice for constructing a comprehensive kernel mass prediction model, with r, SD, and RMSE values of 0.925, 0.0271, and 0.1729, respectively. The methods proposed in this research hold significant application prospects in maize kernel mass detection, providing a crucial foundation for yield detection in mechanized maize harvesting.

Although this study has made certain achievements in establishing a corn grain quality prediction model based on basic geometric features (such as area, perimeter, and circularity), there are still some shortcomings. The limitations of the feature set may affect the comprehensiveness of the model. Future research could consider incorporating more types of features, such as texture and color features, to improve prediction accuracy. Additionally, while the current dataset exhibits a degree of diversity, the application of data augmentation techniques would help enhance the model's robustness. Ablation studies should also be considered to validate the rationality of feature selection and further optimize model performance. Therefore, future research will focus on expanding the feature set, introducing data augmentation, conducting ablation studies, and refining preprocessing steps to enhance the performance and applicability of the corn grain quality prediction model.

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References

1. Tao, J. The adjustment of China's grain cropping structure and its effect on the consumption of water and land resources. *J. Nat. Resour.* **2019**, *34*, 14–25. [CrossRef]
2. Cui, T.; Fan, C.L.; Zhang, D.X.; Yang, L.; LI, Y.B.; Zhao, H.H. Research progress of maize mechanized harvesting technology. *Trans. Chin. Soc. Agric. Mach.* **2019**, *50*, 1–13.
3. Rafiee, M.; Abbaspour-Fard, M.H.; Heidari, A. Analyzing sustainability in bread production: A life cycle assessment approach to energy, exergy and environmental footprint. *Environ. Sci. Pollut. Res.* **2024**, *31*, 46949–46964. [CrossRef] [PubMed]
4. Wu, S.; Zhang, Y.; Zhao, Y.; Wen, W.; Wang, C.; Lu, X.; Guo, M.; Guo, X.; Zhao, J.; Zhao, C. Using high-throughput phenotyping platform MVS-Pheno to decipher the genetic architecture of plant spatial geometric 3D phenotypes for maize. *Comput. Electron. Agric.* **2024**, *225*, 109259. [CrossRef]
5. Xiao, T.; Yang, L.; Zhang, D.; Cui, T.; Wang, L.; Du, Z.; Xie, C.; Li, Z.; Gong, C.; Li, H.; et al. Early prediction of maize resistance to nicosulfuron using hyperspectral imaging and deep learning: Method and mechanism. *Comput. Electron. Agric.* **2024**, *227*, 109511. [CrossRef]
6. Wang, K.R.; Li, S.K. Research progress on corn mechanical grain harvesting crushing rate. *Chin. Agric. Sci.* **2017**, *50*, 2018–2026. [CrossRef]
7. Chen, M.; Jin, C.; Ni, Y.; Yang, T.; Zhang, G. Online field performance evaluation system of a grain combine harvester. *Comput. Electron. Agric.* **2022**, *198*, 107047. [CrossRef]
8. Ferraretto, L.; Shaver, R.; Luck, B. Silage review: Recent advances and future technologies for whole-plant and fractionated corn silage harvesting. *J. Dairy Sci.* **2018**, *101*, 3937–3951. [CrossRef]
9. Harsányi, E.; Bashir, B.; Arshad, S.; Ocwa, A.; Vad, A.; Alsalman, A.; Rịtonyi, T.; Hijazi, O.; Széles, A.; Mohammed, S. Data mining and machine learning algorithms for optimizing maize yield forecasting in central Europe. *Agronomy* **2023**, *13*, 1297. [CrossRef]
10. Ray, D.K.; Mueller, N.D.; West, P.C.; Foley, J.A. Yield Trends Are Insufficient to Double Global Crop Production by 2050. *PLoS ONE* **2013**, *8*, e66428. [CrossRef]
11. Matsumura, K.; Gaitan, C.F.; Sugimoto, K.; Cannon, A.J.; Hsieh, W.W. Maize yield forecasting by linear regression and artificial neural networks in Jilin, China. *J. Agric. Sci.* **2015**, *153*, 399–410. [CrossRef]
12. Mahirah, J.; Kazuya, Y.; Munenori, M.; Naoshi, K.; Yuichi, O.; Tetsuhito, S.; Harshana, H.; Usman, A. Monitoring harvested paddy during combine harvesting using a machine vision-Double lighting system. *Eng. Agric. Environ. Food* **2017**, *10*, 140–149. [CrossRef]
13. Wu, Z.; Chen, J.; Ma, Z.; Li, Y.; Zhu, Y. Development of a lightweight online detection system for impurity content and broken rate in rice for combine harvesters. *Comput. Electron. Agric.* **2024**, *218*, 108689. [CrossRef]
14. Xie, W.; Wei, S.; Zheng, Z.; Chang, Z.; Yang, D. Developing a stacked ensemble model for predicting the mass of fresh carrot. *Postharvest Biol. Technol.* **2022**, *186*, 111848. [CrossRef]
15. Xu, P.; Yang, R.; Zeng, T.; Zhang, J.; Zhang, Y.; Tan, Q. Varietal classification of maize kernels using computer vision and machine learning techniques. *J. Food Process Eng.* **2021**, *44*, e13846. [CrossRef]
16. Zhou, J.; Zeng, S.; Chen, Y.; Kang, Z.; Li, H.; Sheng, Z. A method of polished rice image segmentation based on YO-LACTS for quality detection. *Agriculture* **2023**, *13*, 182. [CrossRef]
17. Sabanci, K.; Kayabasi, A.; Toktas, A. Computer vision-based method for classification of wheat grains using artificial neural network. *J. Sci. Food Agric.* **2017**, *97*, 2588–2593. [CrossRef]
18. Cui, X.; Zhang, P.; Zhao, J.; Xu, W.; Ma, W.; Jin, C. Study on inspection of corn seed breakage based on machine vision. *J. Agric. Mech. Res.* **2019**, *41*, 28–33+84. [CrossRef]
19. Rasmussen, C.; Kirk, K.; Moeslund, T. Anchor tuning in Faster R-CNN for measuring corn silage physical characteristics. *Comput. Electron. Agric.* **2021**, *188*, 106344. [CrossRef]
20. Samrendra, K.S.; Sriram, K.V.; Rakhee, T. Machine learnt image processing to predict weight and size of rice kernels. *J. Food Eng.* **2020**, *274*, 109828.

21. Geng, D.; Wang, Q.; Li, H.; He, Q.; Yue, D.; Ma, J.; Wang, Y.; Xu, H. Online detection technology for broken corn kernels based on deep learning. *Trans. Chin. Soc. Agric. Eng.* **2023**, *39*, 270–278. [CrossRef]
22. Zareiforoush, H.; Minaei, S.; Alizadeh, M.R.; Banakar, A. Qualitative classification of milled rice grains using computer vision and metaheuristic techniques. *J. Food Sci. Technol.* **2016**, *53*, 118–131. [CrossRef] [PubMed]
23. Qiao, M.; Xia, G.; Cui, T.; Xu, Y.; Fan, C.; Su, Y.; Li, Y.; Han, S. Machine learning and experimental testing for prediction of breakage rate of maize kernels based on components contents. *J. Cereal Sci.* **2022**, *108*, 103582. [CrossRef]
24. Fan, C.; Zhang, D.; Yang, L.; Cui, T.; He, X.; Qiao, M.; Sun, J.; Dong, J. A multi-parameter control method for maize threshing based on machine learning algorithm optimisation. *Biosyst. Eng.* **2023**, *236*, 212–223. [CrossRef]
25. Fan, C.; Wang, W.; Cui, T.; Liu, Y.; Qiao, M. Maize kernel broken rate prediction using machine vision and machine learning algorithms. *Foods* **2024**, *13*, 4044. [CrossRef]
26. Chung, S.O.; Choi, M.C.; Lee, K.H.; Kim, Y.J.; Hong, S.J.; Li, M. Sensing technologies for grain crop yield monitoring systems: A review. *J. Biosyst. Eng.* **2016**, *41*, 408–417. [CrossRef]
27. Guan, Z.; Li, H.; Chen, X.; Mu, S.; Jiang, T.; Zhang, M.; Wu, C. Development of impurity-detection system for tracked rice combine harvester based on DEM and mask R-CNN. *Sensors* **2022**, *22*, 9550. [CrossRef]
28. JOHN DEERE. X Series Combines. 2022. Available online: https://www.deere.com/en/harvesting/x-series-combines/ (accessed on 29 October 2024).
29. Gu, Y. Development and Experimental Research of an Online Monitoring Device for Grain Contamination and Breakage Rates in Combine Harvesters. Master's Thesis, Jiangsu University, Zhenjiang, China, 2019.
30. Han, M. Monitoring Method for Grain Contamination and Breakage Rates in Combine Harvesters Based on U-Net Network. Master's Thesis, Jiangsu University, Zhenjiang, China, 2020.
31. Zhang, S. Monitoring Method and Device for Contamination and Breakage Rates of Flowing Grain Based on Multi-Threshold Segmentation. Master's Thesis, Jiangsu University, Zhenjiang, China, 2021.
32. Wu, Z. Research on an Online Monitoring System for Contamination and Breakage Rates of Rice and Wheat Kernels Based on Mask R-CNN. Master's Thesis, Jiangsu University, Zhenjiang, China, 2021.
33. Zhang, Q.; Hu, J.; Xu, L.; Cai, Q.; Yu, X.; Liu, P. Impurity/Breakage Assessment of Vehicle-Mounted Dynamic Rice Grain Flow on Combine Harvester Based on Improved Deeplabv3+ and YOLOv4. *IEEE Access* **2023**, *11*, 49273–49288. [CrossRef]
34. Masithoh, R.E.; Pahlawan, M.F.R.; Arifani, E.N.; Amanah, H.Z.; Cho, B.K. Determination of the Betacyanin and Betaxanthin Contents of Red Beet (*Beta vulgaris*) Powder Using Partial Least Square Regression Based on Visible-Near Infrared Spectra. *Trends Sci.* **2024**, *21*, 7639. [CrossRef]
35. Speiser, J.; Miller, M.; Tooze, J.; Ip, E. A comparison of random forest variable selection methods for classification prediction modeling. *Expert Syst. Appl.* **2019**, *134*, 93–101. [CrossRef]
36. Vladimir, S.; Andy, L.; Christopher, T.J.; Christopher, C.; Robert, P.S.; Bradley, P.F. Random forest: A classification and regression tool for compound classification and QSAR modeling. *J. Chem. Inf. Comput. Sci.* **2003**, *43*, 1947–1958. [CrossRef]
37. Sotiropoulou, K.F.; Vavatsikos, A.P.; Botsaris, P.N. A hybrid AHP-PROMETHEE II onshore wind farms multicriteria suitability analysis using kNN and SVM regression models in northeastern Greece. *Renew. Energy* **2024**, *221*, 119795. [CrossRef]
38. Qiao, M.; Cui, T.; Xia, G.; Xu, Y.; Li, Y.; Fan, C.; Han, S.; Dong, J. Integration of spectral and image features of hyperspectral imaging for quantitative determination of protein and starch contents in maize kernels. *Comput. Electron. Agric.* **2024**, *218*, 108718. [CrossRef]
39. Zhang, H.; Li, Z.; Yang, Z.; Zhu, C.; Ding, Y.; Li, P.; He, X. Detection of the corn kernel breakage rate based on an improved mask region-based convolutional neural network. *Agriculture* **2023**, *13*, 2257. [CrossRef]
40. Luo, N.; Meng, Q.; Feng, P.; Qu, Z.; Yu, Y.; Liu, D.L.; Müller, C.; Wang, P. China can be self-sufficient in maize production by 2030 with optimal crop management. *Nat. Commun.* **2023**, *14*, 2637. [CrossRef]

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