Developing A Machine Vision System for Real-time, Automated Quality Grading of Sweetpotatoes

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Developing A Machine Vision System for Real-time, Automated Quality Grading of Sweetpotatoes

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ABSTRACT. *Sweetpotato is an economically important specialty crop in the United States (U.S.), but it is significantly labor-intensive in many production activities such as postharvest packing. Currently, grading and sorting of sweetpotato storage roots for quality is still performed manually. In addition to incurring high labor costs, manual grading is subjective and prone to human assessment error. This study was aimed to develop machine-vision-based automation technology to reduce labor dependence and costs and enhance quality assessment for sweetpotato packing lines. The developed system consisted of a custom-designed, motorized roller conveyor for sweetpotato transportation and rotation and a computer vision module with a camera to inspect the full-surface quality of sweetpotatoes. A computer vision pipeline with YOLOv8 was developed to segment and track each sweetpotato traveling on the conveyor and analyze quality conditions in real-time. The final grade of individual sweetpotatoes was determined from a sequence of multi-view images against predefined grading standards in terms of size and surface defects. The machine vision system achieved the overall grading accuracy of 88.6% for four classes of samples, suggesting the potential to benefit sweetpotato packers.*

Keywords. *Sweetpotato grading, Machine vision, Automation, Postharvest.*

Introduction

In 2022, sweetpotato production in the U.S. reached 133,000 acres, yielding a farmgate value of approximately $600 million (USDA-NASS, 2023). The major sweetpotato producing states include North Carolina, Mississippi, California, and Louisiana. The sweetpotato crop is primarily produced for fresh market consumption, which constitutes around 90% of its total production value, with the remaining for processing. To enhance marketing strategies and ensure the delivery of superior sweetpotato products to consumers, an essential step in the post-harvest process involves grading and sorting of the harvested sweetpotatoes at packing facilities. This process is to evaluate and grade storage roots for quality characteristics, including size, shape, color, and the presence of any defects.

In the packinghouse, sweetpotatoes undergo a series of handling operations, including immersion in a water tank, thorough washing, elimination of undersized roots and debris, grading and sorting, and box filling (Edmunds et al., 2008). Among these operations, grading and sorting is notoriously labor-intensive, which account for up to 50% of packing line labor costs (Lu et al., 2023). Aside from labor costs, manual grading is subjected to assessment inconsistency due to the subjectivity of human perception and the influence of physiological factors like visual acuity, fatigue, and stress. Moreover, repetitive body movements during manual sorting can lead to musculoskeletal disorders of laborers (Simcox et al., 2001). To enhance competitiveness and profitability of the sweetpotato industry, there is a pressing need to develop labor-saving, automation technologies for sweetpotato grading and sorting.

Computer vision technology offers a promising alternative to manual labor for automated fruit grading and sorting (Bhargava & Bansal, 2021; Bollen & Prussia, 2022; Naik & Patel, 2017). Jarimopas and Jaisin (2008) developed a machine vision sorting system for tamarind pods according to shape, size, and defects, achieving an average sorting efficiency of 89.8%. Nandi et al. (2016) proposed an automated system for grading mangoes based on maturity and quality with an accuracy of nearly 87%. Sofu et al. (2016) reported on an apple sorting for size, color, and weights as well as surface defects achieved sorting accuracy of 79% to 89% at the speed of 0.05–0.2 m/s. Fan et al. (2020) reported on an apple sorting system for defect detection at a speed of 5 apples/s, which achieved an accuracy of 92%. Zhang et al. (2021) developed an apple grading system targeting in-orchard application, which achieved 99% sorting accuracy at a throughput of 10.5 fruits/s during laboratory tests. The sorting system was integrated by Lu et al. (2022) into a harvest-assist and in-field sorting machine and demonstrated in commercial apple orchards. Mohi-Alden et al. (2022) presented a color sorting system for bell peppers, which achieved 93% accuracy for size and maturity at a conveyor speed of 0.2 m/s. Despite these developments for different commodities, to the best of our knowledge, no grading or sorting systems that are dedicated to sweetpotatoes have been reported in literature.

Traditional image analysis based on low-level image processing (e.g., image enhancement, thresholding) and features-based pattern classification have been extensively used in previous studies on fruit grading and sorting. In recent years, deep learning techniques, especially convolutional neural networks (CNNs), have enjoyed unprecedented popularity in handling various visual recognition tasks while attaining remarkable performance (Naranjo-Torres et al., 2020). Among the numerous CNN-based models, You Only Look Once (YOLO) models are presumably the most successful family of object detectors because of their real-time performance, simplicity, and detection capabilities (Terven & Cordova-Esparza, 2023). Several recent studies have explored the application of YOLO-based systems for fruit grading and defect detection. Fan et al. (2022) applied YOLOv4 for online defect detection of apples with accuracy of nearly 94%. Lu et al. (2021) developed an automatic winter-jujube grading robot using YOLOv3, achieving 97.28% accuracy in maturity grading with an average grading time of 1.4 seconds per winter-jujube. Liang et al. (2022) employed semantic segmentation in conjunction with a pruned YOLOv4 network to grade defective apples in real-time, obtaining 92.4% accuracy. Wang et al. (2023) introduced a YOLOv4-based system for classifying different ripeness levels of peaches, incorporating visual and tactile characteristics, achieving 92.2% accuracy for the tactile aspect.

Research is lagging regarding the development of automated grading and sorting technology for sweetpotatoes. Only a handful of studies were carried out on quality assessment and grading of sweetpotatoes. An early attempt was made by Wright et al. (1986) on the assessment of sweetpotato size and shape using simple image processing techniques. Gogineni et al. (2002) reported on image-based sweetpotato quality detection for yield and grading monitoring during harvest, although the field test showed lower grading accuracies (R^2=0.73). Boyette and Tsirnikas (2017) investigated the use of a laser scanner to assess the shape and size of sweetpotatoes but did not give performance metrics. Haque et al. (2021) quantified the shape variations of sweetpotatoes using computer vision approaches including three-dimensional shape reconstruction and feature extraction and whereby classified sweetpotatoes into two classes (“U.S. No. 1” vs “Cull”) with 86% accuracy. Huynh et al. (2022) designed a vision system to measure the volume and weight of sweetpotatoes, which captured top-view images of samples, achieving the accuracy of 96% and 95% in estimating volume and weight, respectively. However, none of these studies was aimed at online quality grading of sweetpotatoes and full-surface quality inspection, which remain critical gaps in the development of automated sorting technology for sweetpotatoes and entail dedicated efforts on fruit transportation hardware designs, real-time computer vision algorithms and integration.

This study is therefore to develop an innovative machine vision system, leveraging the state-of-the-art artificial intelligence (AI) algorithms, for real-time quality grading of sweetpotatoes. The specific objectives of this study were to: 1) develop a hardware prototype for acquiring images online from sweetpotatoes for full-surface inspection. 2) develop a computer vision algorithm pipeline for real-time analysis of size and surface defects of sweetpotatoes; 3) test and evaluate the performance of the proposed system for sweetpotato grading.

Materials & Methods

Hardware System

A machine vision-based grading system was developed for automated, online quality grading of sweetpotatoes. As schematically illustrated in **Fig. 1 (a)**, the system mainly consists of a custom-built motorized roller conveyor, a consumer-grade RGB-D (red-green-blue-depth) camera (RealSense™ L515, Intel Corp., Santa Clara, CA, USA), and a computer. Roller conveyors are commonly used at sweetpotato packing facilities for hand sorting (Lu et al., 2023). A similar, simplified design was used in this study to simultaneously transport and rotate sweetpotatoes [**Fig. 1 (b)**], enabling the presentation of different views of samples to the camera for full-surface inspection. A detailed description of the conveyor system is given in Xu et al. (2023).

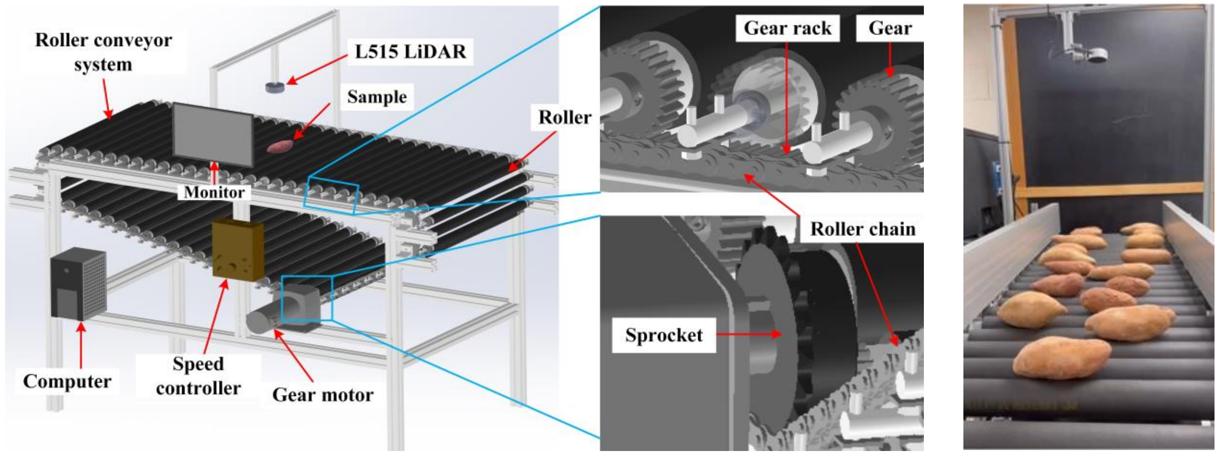

Figure 1. A machine vision-based automated grading system: (a) schematic illustration and (b) a photogram with samples being inspected.

Samples & Image Acquisition

This study experimented on a total of 123 sweetpotato samples in varied quality conditions, purchased from local grocery stores. Each sample was uniquely numbered and evaluated by trained personnel for quality conditions. The length and width of sweetpotato samples were measured using a digital caliper (resolution = 0.01 mm). The defects on the entire surface of each sample were visually examined, and according to the defect severity, sweetpotato samples were categorized into three grades as shown in **Fig. 2**.

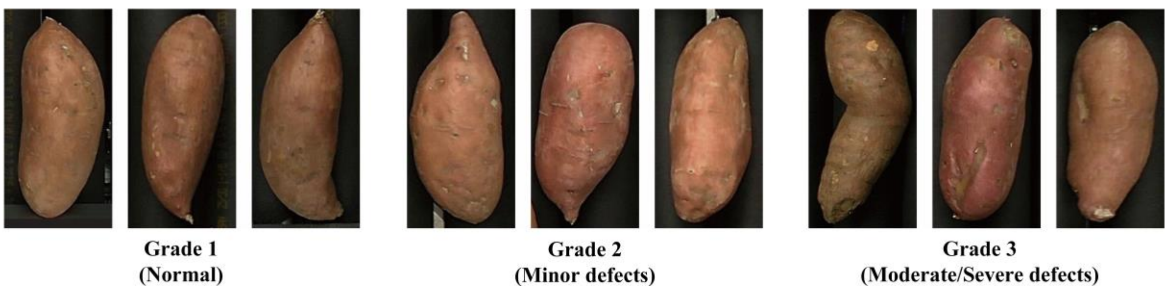

Figure 2. Sweetpotato examples of three grades of surface defects.

During imaging, sweetpotato samples were manually loaded onto the roller conveyor in a continuous manner, batch by batch, at a conveyor speed of 5 cm/s. The camera captured video streams of moving samples at 30 frames per second with a resolution of 1920 × 1080 pixels and in AVI (audio video interleave) format. It should be noted that while the camera acquired both color and depth images, only color images were utilized for sweetpotato grading in this study. The image acquisition was conducted under ambient indoor light conditions (**Fig. 3**). As a result, a total set of 19 videos (corresponding to 19 batches of samples) was captured and used for the analysis described below.

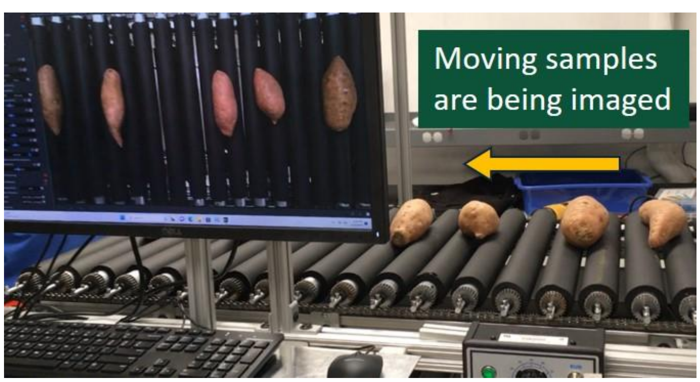

Figure 3. Images are captured from sweetpotatoes moving on the roller conveyor.

Dataset Curation

The video dataset was randomly divided into training (13 videos for 87 samples) and test (6 videos for 36 samples) sets. The sample distribution regarding surface defects is shown in **Fig. 4(a)**. Clearly, the training and test sets contained a very small number of samples classified as Grade 1 (7 samples for training and 1 for testing). To prepare a dataset for developing computer algorithms for sweetpotato segmentation, tracking and grading (described next), a corpus of 15 images was systematically extracted from each video, resulting in a total of 285 images. Thereafter, the image annotation tool, Labelme (https://github.com/wkentaro/labelme), was used to produce polygon annotations for samples (instances) in the images, representing ground-truth masks, each of which was labelled for the grades of surface defects. **Fig. 4(b)** depicts the distribution of annotated sweepotato instances.

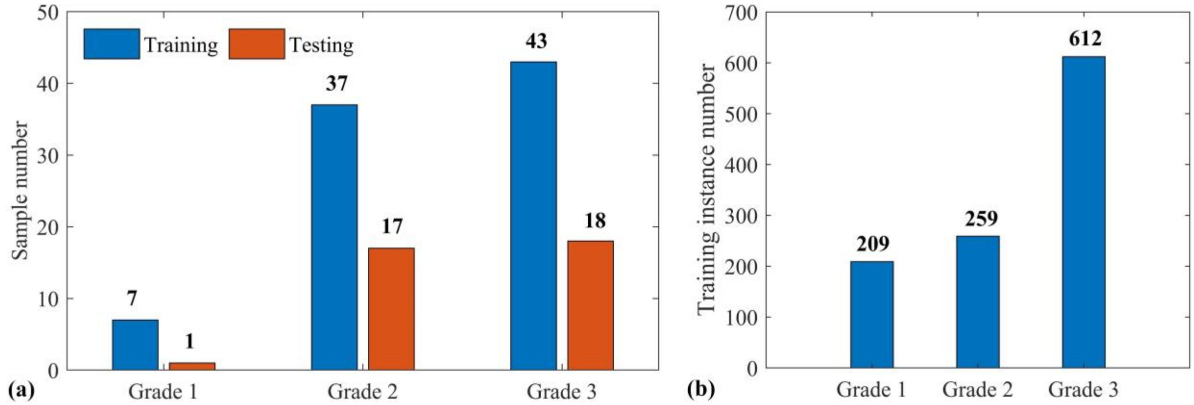

Figure 4. (a) distribution of sweetpotato samples, and (b) distribution of annotated sweetpotato instances in the training set. Grades 1-3 represent varied severity levels of surface defects.

Sweetpotato Segmentation, Tracking, and Grading

Fig. 5 shows the overall computer algorithm pipeline for quality grading of sweetpotatoes. In this study, YOLOv8-s (https://github.com/ultralytics/ultralytics) integrated with the BoT-SORT tracker (Aharon et al., 2022) was trained (with 100 epochs, 5 batches) for real-time instance segmentation and multi-object tracking of sweetpotato samples. The imaging area was purposely divided into three non-overlapping subregions, as illustrated in **Fig. 6**. Within the quality recording region, the samples being tracked underwent quality assessment, including surface defect grading and size estimation, for a sequence of images to ensure complete surface inspection. Upon entering the grading region, the samples were assigned with a final grade according to predefined criteria, which are summarized in **Table 1**, complying with the USDA quality standards of sweetpotatoes (USDA, 2005)

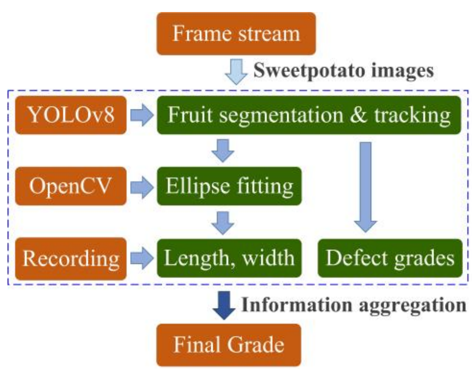

Figure 5. Computer algorithm pipeline for sweetpotato quality grading.

To estimate the length of each sweetpotato, a straight line was established between the two points located at each end of the sweetpotato segment. The maximum measurement perpendicular to its longitudinal axis corresponded to the sweetpotato width. Specifically, the sweetpotao mask was fitted into a ellipse by the *cv2.ellipse()* in OpenCV (2023), from which the lengths of the long and short axes of the ellipse were taken as the length and width in pixel units of the sweetpotato, respectively, which were further converted to quantities in physical units (in inches) based on the pre-estimated spatial resolution of images.

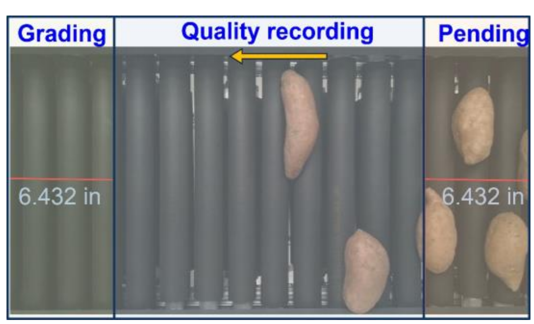

Figure 6. Three distinct subregions of images.

Table 1. Sweetpotato grading standards.

Grades	Length (L)	Width (W)	Surface defects
"**Premium**"	6″≤ L < 9″	W < 3-1/4″	Grade 1, Grade 2
"**Good**"	3″≤ L < 6″	W < 3-1/4″	Grade 1, Grade 2
"**Fair**"		W < 3-1/4″	Grade 3
"**Cull**"	Do not meet the above grading criteria		

As each sweetpotato enters the grading area, a set of information recorded for each instance of the sample is processed, including sample ID that is assigned during tracking, the length, width and surface defect grade of the sample, and the corresponding confidence levels. This set of information is accumulated over a series of images of the sweetpotato traveling in the quality recording region. Here, to determine the final length and width values of the sample, the average measurements were computed for robust estimation. To grade the sweetpotato for surface defect conditions, the Algorithm 1 shown **Fig. 7** was developed, in which the function "combine_measurements" yields the final grade by taking into account a set of surface defect grades for individual segment instances and their corresponding confidence levels. The algorithm starts by initializing a list of potential grades and relevant variables for calculating weighted sums and total confidence. Then it iterates through the given measurements and corresponding confidences, incrementally computing the weighted sum and total confidence for each grade. If a measurement corresponds to "Grade 3" and has a confidence level of 0.9 or higher, the algorithm directly returns "Grade 3" as the final grade. Otherwise, it calculates the weighted average for each grade based on the accumulated confidences and obtains the grading result by selecting the grade with the highest weighted average. The rationale behind the approach (**Fig. 7**) is to account for varying confidences in the measurements and make a more informed decision on the final grade by considering both the measurement data and its associated confidence level.

```
Algorithm 1: Get Finial Grade
  Data: measurements, confidences
  Result: final_result
  Function combine_measurements(measurements, confidences) is
      grades ← ["Grade1", "Grade2", "Grade3"];
      total_confidence ← 0.0;
      weighted_sum ← {grade: 0.0 for grade in grades};
      for each measurement, confidence in (measurements, confidences) do
          if measurement = "Grade3" and confidence ≥ 0.9 then
              return "Grade3";
          weighted_sum[measurement] += confidence;
          total_confidence += confidence;
      weighted_average ← {grade: weighted_sum[grade] / total_confidence for
        grade in grades};
      final_result ← max(weighted_average, key=weighted_average.get);
      return final_result;
```

Figure 7. Pseudocode for determining the final surface defect level of sweetpotatoes.

To assess segmentation performance, the mask mAP50 was calculated during model training and testing. The grading accuracy was assessed at both instance and sample levels. The instance-level accuracy measured the performance in grading segmented sweetpotato instances for surface defects regardless of their sample ID. The sample-level accuracy was calculated for individual samples regarding size and surface defects over multiple images as described in **Fig. 8**, representing the major performance metric. These metrics were calculated as follows:

$$\text{mask mAP50} = \frac{1}{N}\sum_{i=1}^{N}\text{AP}_{50}^{(i)} \tag{1}$$

$$\text{Instance Grading Accuracy} = \frac{\text{Number of Correctly Graded Instances}}{\text{Number of Total Tested Instances}}\times 100\% \tag{2}$$

$$\text{Final Grading Accuracy} = \frac{\text{Number of Correctly Graded Samples}}{\text{Number of Total Tested Samples}}\times 100\% \tag{3}$$

where N is the total number of training instances and $\text{AP}_{50}^{(i)}$ denotes the average precision at 50% IoU (intersection over union between the predicted mask and ground truth mask) for class i.

Computer algorithms in this study were implemented with the aid of PyTorch (version 1.14) and YOLOv8 for sweetpotato segmentation, tracking, and defect detection, and OpenCV (version 4.5.3) for sweetpotato sizing. These algorithms were run on a computer with an i7-9750H CPU @2.6 GHz processor and NVIDA GeForce RTX 2060 GPU in Windows 11 OS.

Results

Instance Segmentation and Defect Grading

Fig. 8 shows the training curves of mask mAP50 of YOLOv8s for sweetpotato surface detection. The model exhibited a rapid convergence, reaching the accuracy of 77.7% within 100 epochs. The testing performance of the YOLO model in grading sweetpotato instances is shown in the row-normalized confusion matrix (Fig. 10). The YOLOv8s attained an overall instance grading accuracy of 72.3%.

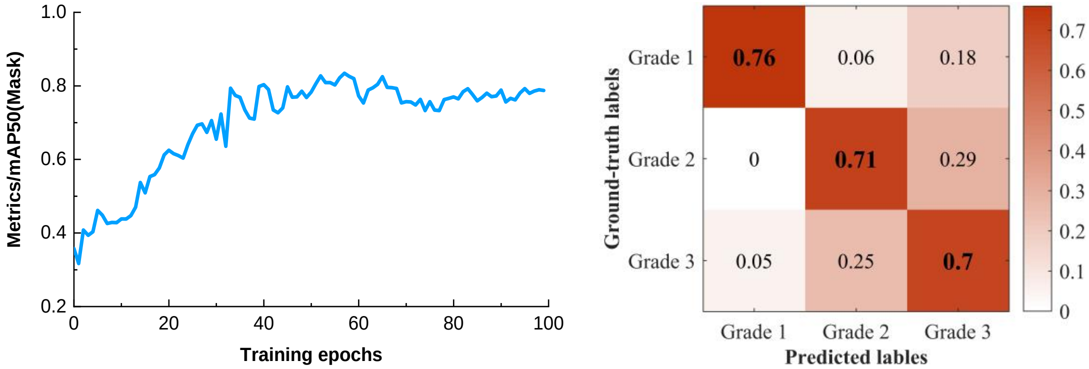

Figure 8. Training curves of mAP50 of YOLOv8s (left) and the confusion matrix of testing instances (right).

The sweetpotato grading pipeline was implemented and evaluated on four testing videos. **Fig. 9** presents example frames from one of the test videos (https://youtu.be/0QWdWN6p54g), visualizing the detected bounding boxes, segmentation masks, the estimated length and width, the surface defect grade, and the associated confidence for each sweetpotato instance. The YOLOv8s-based pipeline for sweetpotato segmentation and tracking, which was implemented at about 28 ms per frame, performed quality assessment for each fruit segment in real time. As samples were moving forward while rotating within the quality recording region (**Fig. 6**), the grading system dynamically estimated sample size and determined surface defect grades, enabling the entire surface of samples to be adequately assessed.

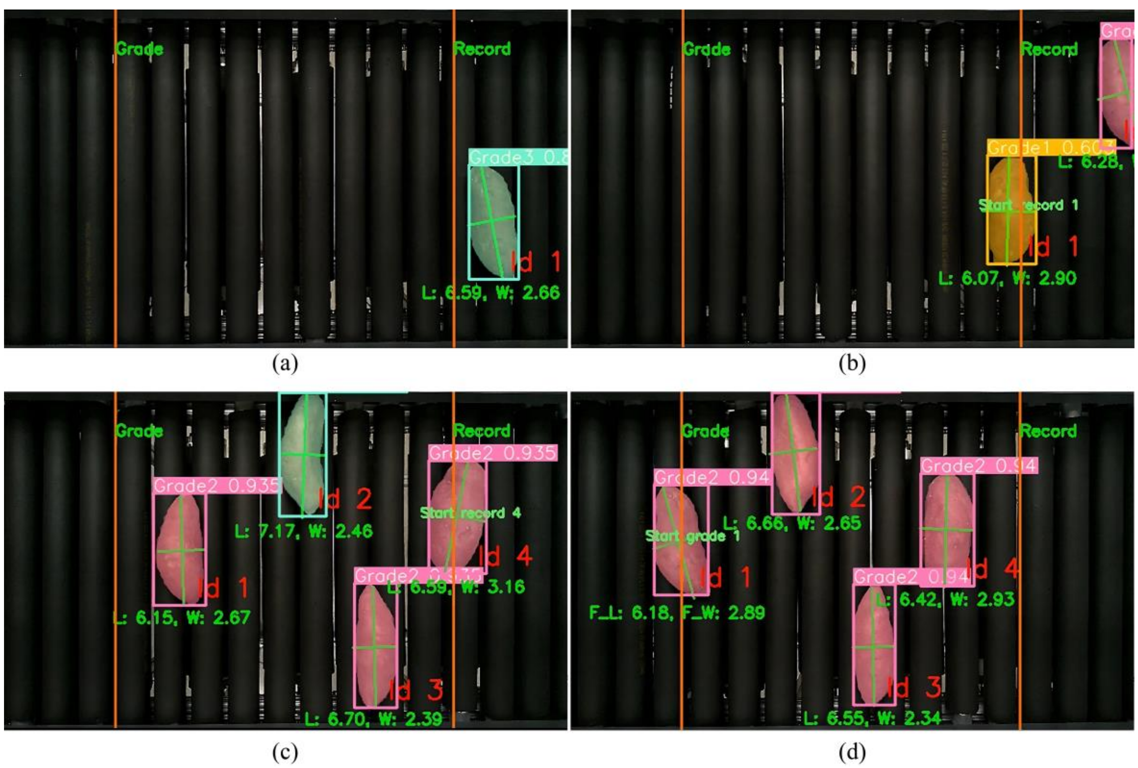

Figure 9. Clips from the test video. (a) sweetpoato enters the pending region where the grading process is initiated (b) sweetpotato enters the quality recording region where its quality information is continuously recorded. (c) sweetpotato continues to rotate forward, ensuring coverage of its entire surface for quality assessment. (d) sweetpotato enters the grading area where a final grade is assigned to individual samples.

Size Estimation

Percentage accuracies of 95.1% and 89.4% were obtained for the estimation of the length and width of sweetpotatoes, respectively, as shown in **Fig. 10**. One possible reason for the lower width estimation accuracy lies in the method used for ground-truth measurements, which is based on the "Maximum diameter". The elliptical short axis derived from the ellipse fitting could not precisely represent this measurement. Nevertheless, the length estimation accuracy was encouraging, given only simple processing was done for this task. Improvements are possible by employing machine learning approaches, as done in a prior study for sweetpotato volume estimation (Xu et al., 2023).

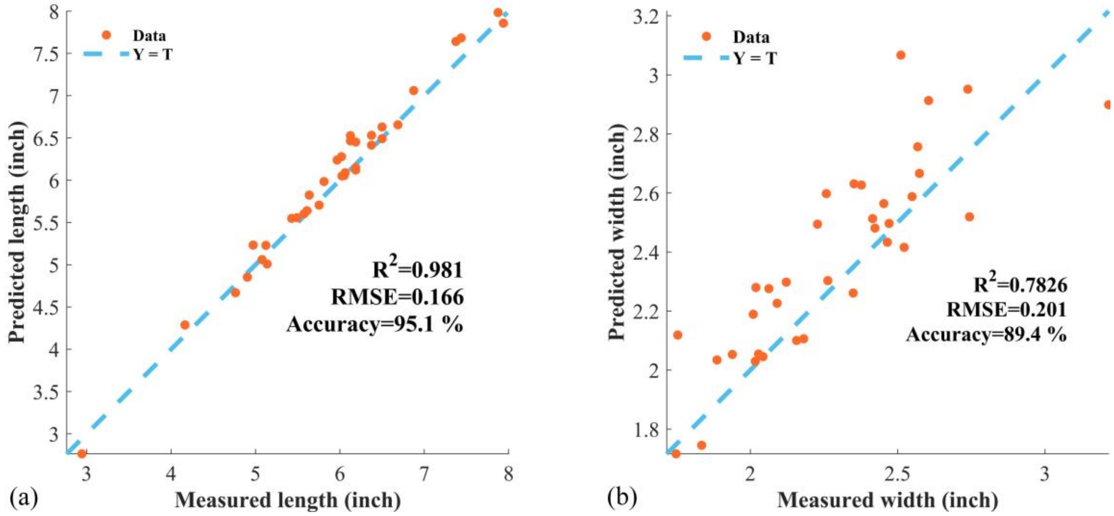

Figure 10. Sweetpotato size prediction results: (a) length. (b) width.

Sample-Level Quality Grading

Fig. 11(a) depicts the sample-level grading result in a row-wise normalized confusion matrix. The grading factored both sweetpotato size and surface defect grades as defined in **Table 1**. The overall grading accuracy was 88.6%, with only four samples misgraded. Upon the examination of source errors, the primary source consisted in the detection of surface defects, which was resposible for 75% of grading errors as shown in **Fig. 11(b)**. From the confusion matrix, grading sweetpotatoes of the intermediate "Good" grade yielded the lowest accuracy of 72%, presumably because of the subtle differences between the "Good" grade with both “Premium” and “Fair” grades. It is also noted that, the length estimation, despite relatively good accuracy (**Fig. 10**), contributed to 25% of grading errors. In contrast, the poor width estimation had minimal impacts on the eventual sample grading, because the estimated width values were still far below the width threshold (that is 3.25 inches) in the grading criteria (**Table 1**). It is possible to enhance the overall grading accuracy by collecting a larger set of sweetpotato samples with diverse quailty conditions in terms of both size and surface defects.

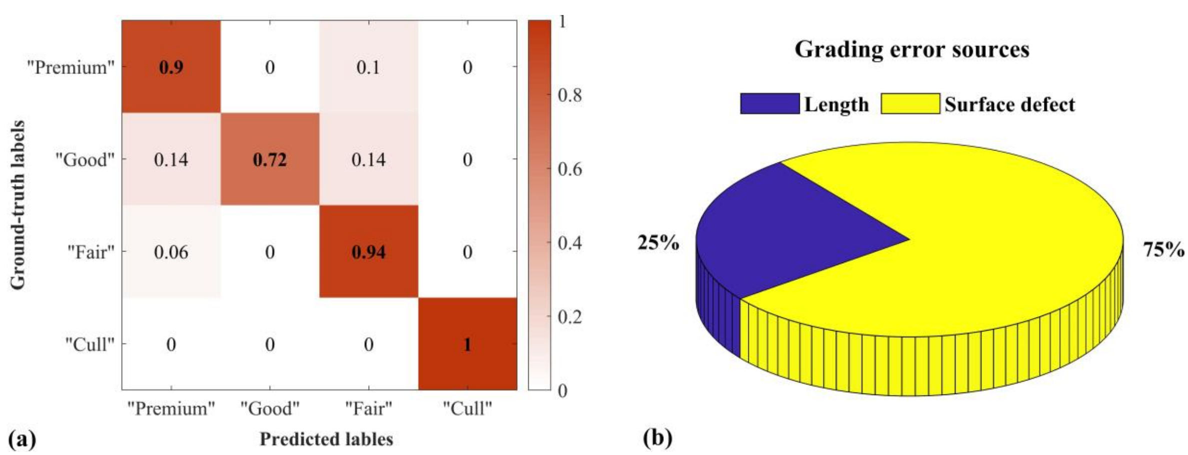

Figure 11. (a) Confusion matrix of testing samples, and (b) grading error sources of testing samples.

This study represents the first attempt to develop a machine vision sytem dedicated to automated grading of sweetpotatoes. A computer algorithm pipeline based on YOLOv8s was developed for sweetpotato segmentation, tracking, and surface defect grading. It however produced a relatively low grading accuracy, which can be attributed to two primary factors. Firstly, the YOLOv8s has limited parameters and layers among YOLOvs models, potentially restricting its learning capacity. The peformance of larger YOLOv8 models and alternative architectures is worthy of investigation. Secondly, only a small number of sweetpotato samples were examined in this study, and the samples, which were purchased in local grocery stores, had limited quality variations since they had been subjected to sorting operations at packing facilities before entering the marketplace. It is more desirable to experiment a large set of freshly harvested sweetpotato samples with a broader spectrum of quality conditions, which has the potential to strengthen the grading system's reliability and generalizability. Furthermore, the endeavors towards real-time implementation and optimization in imaging remain an ongoing pursuit, characterized by several unaddressed aspects. These challenges encompass multifaceted dimensions such as grading/sorting throughput and a quantitative understanding of the surface inspection process, intertwined with influential variables like roller speed, frame sampling rates, and working area. For instance, the conveyor speed could potentially influence the tracking performance of sweetpotatoes and consequently the final grading results. Furthermore, the size of the area where the sweetpotato sorting operation takes place (conveyor size) is crucial in determining the sampling frequency since it affects accessibility and processing time.

Overcoming the challenges identified above necessitates concerted efforts in software and hardware advancements, along with rigorous optimization and extensive validation tests. Hardware improvements should focus on refining the conveyor sytem to accommodate high-speed, high-throughput operations, and possibly implementing more powerful mulitspectral imaging technology. The in-depth validation framework should cover a wide range of real-world scenarios to ensure the robustness and reliability of the grading system under different conditions. Moreover, it is imperative to integrate the grading system with sorting mechnisms to fully realize automated grading and sorting of sweetpotatoes. This will needs dedicated efforts that combine advances in AI with technological innovations in sorting designs and prototyping to build a full-fledged sweetpotato sorting system towards practical applications.

Conclusion & Future Research

This research presents a novel machine vision system for automated, online quality grading of sweetpotatoes. Through implementing a YOLOv8s-based computer algorithm pipeline, the system achieved real-time tracking and defect grading of sweetpotatoes and simultaneously estimated sweetpotato size (length and width), from multiple-view images for full-surface inspection. Experimental evaluation yielded an overall sample grading accuracy of 89%, factoring both size and surface defects in the sample grading. Research is ongoing to enhance the grading accuracy and validate the system performance under higher conveyor speeds and larger sets of sweetpotato samples. Future investigations will focus on the development of a full-fledged system with sorting mechanism integrated towards real-world applications.

Acknowledgments

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