A Deep Learning Approach to Detect Severity of Mango Damage in the Early Fruit Stage

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ABSTRACT

Accurate detection of mango fruit damage predominantly from fruit fly infestation is pivotal as it directly affects both yield and trade worldwide. Therefore, timely identification of such damage is critical to mitigating the spread of infestation and minimizing associated losses. This paper focuses on the early detection of mango damage in orchards using YOLOv8 models, that offer enhanced accuracy and speed compared to earlier versions, making them more efficient for object detection tasks. Limited studies have been done to detect and classify damage on fruits in orchards using deep learning, with the need for more models to detect various categories of damage instances. The experiments in this study revealed no substantial differences among the various YOLOv8 versions used with the highest accuracy of 88.6% and 98.5% attained for detecting damage and mango instances respectively. Both YOLOv8s and YOLOv8l obtained a precision value of 88.6% for lesion detection, and 87.9% using YOLOv8x. However, YOLOv8x achieved slightly higher values of recall and mAP compared to other models in detecting damage features. The study has further revealed that learning the damaged features of mango fruit is more challenging compared to healthy features, as observed from values obtained from the precision-recall curve. Through fine-tuning parameters of the models, our experimental results using the YOLOv8 model demonstrate the potential of lesion detection on mango fruits on trees, leveraging a dataset of 1317 images augmented to 3161. This study addresses the challenge of estimating profits and losses for fruits still on trees, which has been relatively overlooked in prior research efforts. We believe this method can effectively be adapted to detecting lesions on other fruits in orchards with minimal modifications. Future work can consider a better dataset with minimal noise while exploring different growth stages of fruits, and weather conditions the data is captured using alternative models while incorporating other factors in the segmentation and analysis phases.

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CCS CONCEPTS

• **Computing methodologies** → *Machine learning*.

KEYWORDS

Fruit detection, damage detection in mangoes, YOLOv8 variants, YOLOv8s, YOLOv8l, YOLOv8x, deep learning

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1 INTRODUCTION

Mango damage is mostly attributed to fruit fly pests that have become a major constraint in production and marketing, with its management cited as a challenging issue reported worldwide [13, 39]. Plant pests and diseases have been seen as a constant dilemma as they can significantly degrade the quality and reduce the quantity of agricultural products [35]. Generally, diseases and pests are cited as a major hindrance to the production and marketing of fruits, with their management seen as a challenging issue [32, 34, 36] worldwide as pests can diminish production and sometimes even endanger the orchards [3, 58]. These pests cause lesions on fruits, inflicting damages on them, which require knowledge and the expertise of farmers to analyze them [36]. One significant issue facing the horticultural industry in developing nations is pests such as fruit flies which are the most destructive, causing much waste in mangoes fruits [34] due to damages that range from 30% to 100%.

Annually, a large portion of fruits to be exported encounter rejection due to damage induced by pests and diseases, causing losses for farmers. This is due to quarantine restrictions imposed by fruit-importing countries, which hinder horticultural trade. The impact is particularly notable in markets between developing and developed countries [34]. As a result of such damage to fruits, diseases and pests have imposed substantial danger to farming, causing deterioration of the quality of fruits in orchards [53]. This has called for the need to alleviate challenges associated with manual methods of assessing and investigating damage to determine fruit quality, which is based on the visual experiences of trained professionals [8, 27, 42]. Generally, many agricultural areas require proper monitoring [5] yet the conventional methods employed in evaluating the status of fruits for diagnosing pests and diseases [9, 33, 52, 55] face limitations, notably the inability to independently extract features from used datasets and work with large datasets. They rely on visual inspection by human experts to identify visible symptoms, microscopic examinations of morphological features, and the utilization of molecular and microbiological diagnostic techniques [35]. These traditional methods are normally tedious [8, 27, 42] a process featuring low efficiency, thus the need for automated approaches to quickly and accurately detect and diagnose fruit lesions [54] that leave visible features on the surface that represent damages to fruits. These features include blemish defects, and symptoms of skin rub with discoloured or black areas of a healed scar on the skin observed on mango fruits [16]. While traditional methods may appear to be more accurate and reliable, they are associated with hurdles that require consultation with domain experts and depend largely on their availability. This has sparked great research aimed at automated monitoring of fruits to prevent the severity of damage and loss. With the advancements in computer vision and image processing technologies, it is now feasible to use optical sensors for capturing image datasets of fruits to be monitored in evaluating their health conditions [36]. In a similar manner, the recent era of real-time and nondestructive approaches to pest and disease recognition makes essential use of conventional machine vision techniques that use shallow learning. This has provided promising solutions for various tasks in fruit assessment processes such as detection and classification, among others [4]. However, as a result of the advent of state-of-the-art deep-learning techniques that are recently preferred due to their ability to extract features automatically [37, 58, 59], several cutting-edge models including different variants of VGG, DenseNet, ResNet, YOLO and Inception among others [14, 15, 29, 58], have shown more outstanding performance for evaluation of fruits' status. This is in line with what the horticulture sector urges. The fruit industry recommends a proactive approach to detecting damages and the associated conditions to prevent their spread from one fruit to another. This helps reduce the likelihood of substantial decreases in expected fruit yield, preventing significant economic losses [23, 32]. Furthermore, timely detection of diseases in the agriculture sector is a decisive precondition for taking corresponding control measures [50].

As such, this study aimed at developing deep learning models using YOLOv8 variants in automated damage severity detection during an early fruiting stage in mango orchards.

Studies embracing both classical machine learning [2, 4, 43, 44] and deep learning techniques [15, 25, 38, 58] for automated damage detection in fruits are reviewed. However, classical machine learning faces criticism for its manual crafting of features and lack of robustness in managing large datasets, which has led to a growing demand to explore cutting-edge deep learning-based approaches [28]. However, it should be remarked that most of these studies have been attempted at post-harvest [2, 27] and thus estimating profits and losses for fruits still on trees is a challenging area that requires more attention.

Furthermore, most studies done on fruit assessment in orchards have focused on detection [6, 7, 19, 21, 30, 40, 45, 47, 51, 56, 57] and yield estimation [17] using different imaging modalities, including UAV and phone-based imaging. However, limited studies have taken a further step in analyzing the status of the detected fruits. Below, we present a discussion of past work done on damage detection and assessment of fruits in orchards.

Zhang et.al [58] proposed a deep learning-based algorithm for the identification of canker, anthracnose, sunscald, greening, and melanose citrus diseases in orchards. The algorithm had a detection network using YOLO-V3, YOLO-V4 and Optimised YOLO-V4 models to detect the citrus fruit in the background. The classification network included MobileNet-V2, ResNet-50, DenseNet-169 and EfficietNet-B4 to classify fruits. These were tested on 1524 images from orchards. The optimised YOLO-V4 model was best for detection with an accuracy of 0.890 and the EfficientNet model for classification with an F1 score of 0.872. Tian et.al [49] then proposed an image processing approach to identify lesions of green apples using GABPNN to obtain binary images, then the region of interest using SVM, attaining an accuracy of 92.1%. Tian et.al [50] further utilised DenseNet in conjunction with the YOLO-V3 model to enhance its performance in detecting anthracnose lesions on apple surfaces in orchards. The cycle-consistent adversarial network algorithm was used for the augmentation of the dataset, which had 140 images of diseased apples and 500 healthy images. The model performed better than Faster R-CNN, with VGG16 NET and YOLO-V3 attaining an F1 score of 0.816, an IoU of 0.917, and an average detection time of 0.032 s.

The majority of studies done on fruit damage assessment have been in the post-harvest phase using image processing, traditional machine learning [1, 2, 4, 12, 31, 44] and deep learning [14, 25, 58]. For instance, a study done in [15] attempted to identify citrus fruit damage induced by fruit flies using CNN-based ResNet-50, GoogleNet, VGG-16 and AlexNet models, with AlexNet using SGDm attaining the highest accuracy of 99.33% using the 1519 image set.

1.1 Research Contribution

The major contributions of this work include:

(1) A dataset comprising early-fruiting mango fruits from different varieties, exhibiting various kinds of damage instances in an orchard setting. It should be noted that existing datasets have primarily been in the post-harvest phase, making this dataset a unique contribution.
(2) A damaged early-fruiting mango detection method has been developed using three variants of the YOLOv8 model, namely YOLOv8s, YOLOv8l, and YOLOv8x. The models have especially been developed to detect these damages on mango fruits while they are still on the trees.

In the first part of this paper 1, we introduce the background, objectives, and past research work on object detection in fruits and associated damages using deep learning approaches. In the second part, 2, we will introduce the materials and methods employed in this study and the YOLOv8 model. In the third section 3, we analyze the experimental results and discuss the findings of the study. Finally, we summarize our contributions to this paper in the conclusion and then suggest future research directions that researchers may explore 5.

2 MATERIALS AND METHODS

2.1 image data acquisition

In this study, images were captured using a smartphone with a camera whose pixel resolution was 3000 × 4000. The images were for mangoes in the early fruiting stage. An orchard in the National Crops Resources Research Institute (NaCRRI) in Namulonge, Uganda, was selected. The images were collected randomly during different weather conditions, including sunny and cloudy, at different times: morning, afternoon, and evening. 1700 images were collected in the orchards. Pre-processing was applied to clean the dataset, resulting in only 1317 images that met the criteria. Some of the images used have a single fruit, and others have clusters.

2.2 Image annotation

A dataset of images was uploaded in Roboflow and annotated using the polygon tool. Two classes were created: damage and healthy to represent the mango fruit's affected and healthy parts, respectively. This study managed to find entomologists who assisted in identifying the lesions on the fruits. Three individuals participated in the annotation of the image dataset, with the third mainly involved in validation tasks to ensure that they were accurate and complete. The resultant image set was then augmented using various techniques to increase the diversity and size of our dataset.

2.3 Image pre-processing done

2.3.1 Auto-orient. Auto-orient was applied to correct the orientation of the images to leverage metadata embedded in them, such as information about whether the image file was taken in landscape or portrait mode.

2.3.2 Image Resizing. Resizing was applied to better process the collected images. The dataset used was resized to 640 × 640 pixels.

2.3.3 Image data augmentation. This helped to obtain a reasonable dataset [24, 46], augmentation was seen as a necessary procedure in this study to obtain enough data for training our models. Several techniques were randomly applied to the dataset of 1317 images, resulting in 3161 images. Several techniques used are discussed below.

(1) Rotation. In this study, the images were rotated 90 degrees clockwise and 90 degrees counter-clockwise between 15° and -15° using the Roboflow tool.

(2) Translation. This involves Shifting images left, right, up, or down to perform a transformation to avoid positional bias in the data [46].

(3) Cropping. This is a processing step for magnifying the original image [22, 24].

(4) Flipping. The images were flipped either horizontally or vertically.

2.4 YOLOv8

YOLOv8 released by Ultralytics is the latest state-of-the-art model in the family of YOLO [18] used for various tasks, including object detection, image classification, and instance segmentation tasks. YOLOv8 includes numerous architectural and developer experience changes and improvements over YOLOv5. YOLO was introduced to the computer vision community in 2015 [41]. Since its inception in 2016 to date, the YOLO family has continued to evolve, with the latest being YOLOV8. YOLOv8 presents five scaled variants, including YOLOv8n (nano), YOLOv8s (small), YOLOv8m (medium), YOLOv8l (large), and YOLOv8x (extra-large) showing how it outperforms its predecessors [48]. YOLO-v8 and YOLO-v5 exhibit outstanding real-time performance. From initial benchmarking results from Ultralytics, there is a strong indication that YOLO-v8 is poised to excel in constrained edge device deployment, stressing its high inference speed [20].

3 EXPERIMENTS AND DISCUSSION

The YOLOv8 models built in this study were trained on a GPU - 1 x NVIDIA Tesla T4 server with resources of 16 cores, 110 GB RAM, 352 GB of disk, and an OS Type-Linux. An annotated dataset was uploaded to the Azure Datastore. The Azure Machine Learning custom environment was then used to build the machine learning models. OpenCV, a computer vision library was used in this study for several tasks including reading and resizing images, drawing bounding boxes, and saving annotated images. To improve the detection accuracy of the model and to adapt the input required for the YOLOV8 model, the input images were adjusted to 640 × 640 pixels. Taking into account the resources of the server, such as memory constraints, the batch size was set to 16, as enough space was available using 300 epochs. Other parameters used in this study, such as the initial learning rate and optimizer, among others, refer to the original parameters in the YOLO-V8 model.

3.1 Parameter Test

During experiments carried out in this study, the parameter batch_size is set as 16, IoU 0.7, initial learning late 0.01, and the epoch is set as 300, as realised in Table 1. However, early stopping was realized in all models built at 127, 153, and 178 epochs for YOLOv8s, YOLOv8l and YOLOV8x respectively, with a patience value of 50 in all cases.

3.2 Indicators to evaluate models developed

(1) Precision which measures the total number of positively predicted classes that belong to the number of positive classes.
(2) Recall. This shows the number of correct predictions made out of all the optimistic predictions that could be made.
The precision-recall curve is then obtained by using the precision ratio as the vertical axis and the recall ratio as the horizontal axis.
(3) Loss Function. This evaluates the difference between predicted values and actual values, guiding the optimization process in deep learning models.
(4) Detection Time. The average detection times for several deep-learning models were compared in this paper, and the real-time performance of these models was analysed.

Table 1: Initial Parameters used in building the YOLOv8 model variants

size of input images	Batch size	Initial learning rate	Epochs	Optimiser	IoU
640 x 640	16	0.01	300	Auto	0.5

3.3 Model Evaluation and Performance Analysis

Several parameters supported by YOLOv8 were adjusted to enhance the performance of the model. Through these adjustments, such as increasing the number of iterations or training steps, the loss function curve gradually becomes convergent with the increasing cycle.

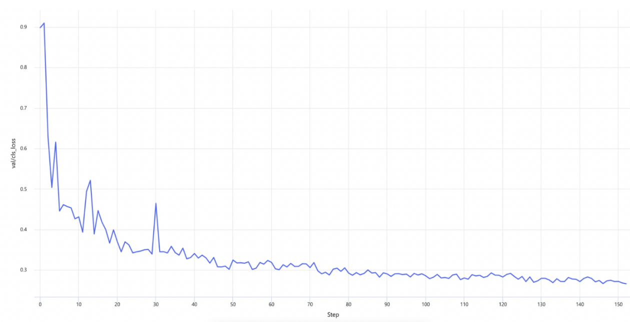

Figure 1: Training loss curve for YOLOv8l

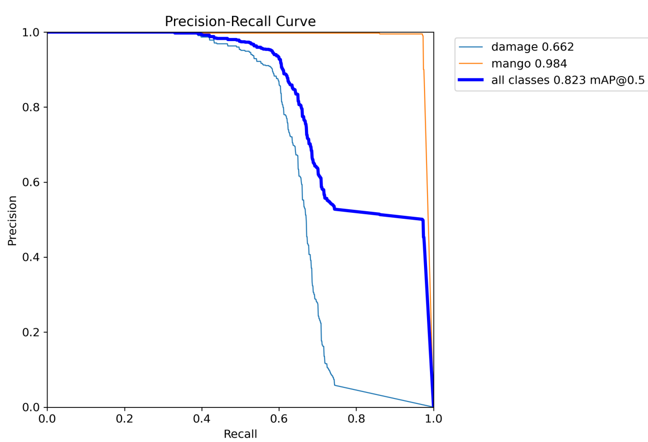

Figure 2: Results of Precision-Recall Curve for YOLOv8x

3.4 Severity detection on the fruit

The models developed in this work were able to compute for severity of damage detected and quantify that damage which can aid in grading mangoes in orchards. A standard was developed by a local expert as in Table 3 to categorise the damage identified on the mango. Several other standards have been created by different experts to aid in grading mangoes [12]. For instance, the technical staff from An Giang University and Vietnam National University [10] and All India Co-ordinate Research Project [26].

The severity of damage detected on the mango fruit was computed as:-

$$\text{Severity} = \frac{\text{Total area of damage on the fruit}}{\text{Total Area of the fruit}} \times 100 \qquad (1)$$

For each image captured on the tree in the orchard, the model developed can identify damaged instances (shown in Red colour) and healthy instances shown in green colour. Using the computation in equation (1). Results obtained from the model were:- Total Damage Area: 13,359.0, Mango Area: 23,725.0, Severity Level: 36.0%. This study used an expert to draft a scale to categorise damage as seen in Table 3.

3.5 Area of the fruit and damage instances

(1) Computing area of the mango
The area of the mango fruit is calculated by utilizing the polygon annotations of the model associated with each mango instance. This process involves converting polygon vertices into areas, providing an accurate and quantitative measure of the spatial extent of the mango fruit within each image.

(2) Computing area of the Damage instances on the mango
This area is acquired from polygon annotations of each damage instance. This can later be used in quantifying the extent of damage, supporting severity analysis.

3.6 Masking mango images

3.6.1 Polygon to Mask Conversion. The masking process starts with the conversion of polygon annotations into binary masks. This pivotal step is achieved through the utilisation of the OpenCV library, employing the polygon_to_mask function. The function precisely fills polygonal regions, generating binary masks that help to delineate the regions of interest within annotated instances.

3.6.2 Background Removal. Following the conversion of annotations into binary masks, a bitwise operation is applied. This operation strategically removes background pixels, leaving behind isolated instances. The refined dataset resulting from this procedure significantly enhances its quality by providing cleaner instances. This, in turn, optimises the efficiency of subsequent model training.

3.6.3 Severity Grading. An integral aspect of the masking process is the assessment of the severity of damage within each annotated instance. This is accomplished by calculating the percentage of damaged area of the mango fruit. Severity levels are then assigned, categorising instances into "Healthy", "Low", "Intermediate," or "High." This nuanced severity grading provides valuable insights into the degree of damage within segmented objects, offering a comprehensive understanding of the dataset.

Table 2: Evaluating model performance with different metrics

	Models:-	YOLO-v8s			YOLO-v8l			YOLO-v8x		
No:		All class	Damage	Mango	All class	Damage	Mango	All class	Damage	Mango
1	Precision	93.0	88.6	97.5	93.6	88.6	98.5	93.1	87.9	98.2
2	Recall	77.9	58.7	97.1	77.8	58.2	97.4	78.3	59.3	97.4
3	mAP	81.8	65.5	98.1	82.1	65.8	98.3	82.3	66.2	98.4
4	Average run-time	2h 3m 34.77s			7h 2m 36s			2h 3m 34.77s		

Table 3: Category to grade damage in this study

% area affected	**Category of Damage**
No infection	Healthy
1 – 25 percent	low
26 – 50 percent	Intermediate
More than 50 percent	High

Figure 3: Severity detection on a cluster of fruits

3.7 Comparison of different detection models

From results presented in Table 2, YOLOv8l has demonstrated superior performance, achieving the highest precision scores of 98.5% and 88.6% for detecting mango and damage instances, respectively. This performance slightly outperformed that of YOLOv8x. However, when considering recall and mAP as performance indicators, YOLOv8x exhibited a slight edge over YOLOv8l. Notably, both YOLOv8x and YOLOv8l outperformed YOLOv8s in all instances.

Overall, this study has demonstrated that YOLOv8x is the best using mAP which is a suitable metric recommended for a general assessment of YOLOv8 model performance [11]. It attained 98.4% in detecting mangoes compared to 98.3% and 98.1% attained using YOLOv8l and YOLOv8s respectively. More so, it had the highest value of 66.2% in detecting damage instances compared to 65.8% and 65.5% attained using YOLOv8l and YOLOv8s respectively. Generally, learning to detect damage instances posed a significant challenge compared to learning the healthy features of the mango fruit.

4 DISCUSSION OF RESULTS

In this study, we have presented findings on the automated detection of mango damage severity during the early fruiting phase in orchards while employing YOLOv8 deep learning-based techniques. The results obtained demonstrate the feasibility of automatically quantifying damage to fruits while they are still on the trees before harvest. Based on the results obtained using the precision-recall curve, it is evident that learning damaged features is more challenging compared to healthy features of the mango fruit. Additional support for the challenge in learning damage features is apparent in the mAP, precision, and recall values detailed in Table 2, where values for damage detection are consistently lower than those for the healthy section across all three variants of the YOLOv8 model (YOLOv8s, YOLOv8l and YOLOv8x) used in this work. Notably, our research has shown no significant difference in the performance of the three models under consideration, as confirmed by the analysis using metrics including Precision, Recall, and mAP, as indicated in Table 2.

5 CONCLUSION AND FUTURE WORK

To facilitate the automated detection of damaged mangoes in the early fruiting phase in an orchard setup, this piece of work presents an approach based on YOLOv8s, YOLOv8l and YOLOv8x models. These were trained on a dataset of 2,800 images and evaluated on 132 images. The experimental results demonstrate that the models are capable of recognising both the mango fruit on the tree and the lesions on detected fruit with a high level of accuracy, as indicated by the Precision scores of 98.5% and 88.6% for mango fruit and damage instances, respectively, which were attained using the YOLOv8l model. However, although the model performs well on damage instance detection, we observed some limitations with how well the masks for damage instances predicted by the models relate to the ground truth masks. In future work, we hope to attain a better dataset with limited noise considering the various growth stages of the different varieties of fruit and the weather conditions under which the data is obtained. Future work will also involve investigating the performance of other models other than the YOLOv8 variants. We shall further be able to include additional factors, such as size and number of lesions on the fruit during the segmentation phase of the lesions on the identified fruit. This development could offer deeper insights for mango breeding experts. Finally, we believe the models developed in this study can easily work on other similar fruits, such as the citrus fruits in the orchard set-up, by applying minimal modifications.

DATA AVAILABILITY

The dataset used in this work is not publicly available for the time being, but upon request, the authors are willing to share.

CONFLICTS OF INTEREST

The authors claim no conflict of interest regarding the publication of this piece of work.

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