Ain Shams Engineering Journal 16 (2025) 103735

Contents lists available at ScienceDirect

Ain Shams Engineering Journal

journal homepage: www.sciencedirect.com

Full Length Article

Analysis of the impact of damage rate on the performance of orange fruit harvesting robot

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ARTICLE INFO

Keywords:
Fruit harvesting robot
Occlusion
Damage rate
Fruit bruise
Fruit orientation
Illumination

ABSTRACT

Reducing damage rates is paramount for optimizing the efficiency of fruit harvesting robots and advancing their journey towards commercial viability. Despite the crucial role that damage rates play in determining fruit quality and marketability, there is a notable lack of comprehensive and in-depth studies analyzing this aspect, especially within the context of fruit harvesting robots. Most research tends to prioritize metrics such as success rate and accuracy of fruit picking, leaving the examination of damage rates relatively overlooked. This study fills this gap by conducting a thorough examination of the factors contributing to damage rates in fruit harvesting robots, including the causes of damage, the types and sizes of bruises incurred, and the impact of occlusion, illumination conditions, and end effector orientation. Additionally, the research investigates strategies for minimizing damage rates, offering insights into optimizing fruit harvesting techniques to reduce potential damage. Occlusion, illumination, and gripper angle were found to significantly influence fruit damage. Specifically, a 10 % increase in occlusion raised damage by 1.18 %, a 100 Lumen/m^2 increase in illumination reduced damage by 10.5 %, and deviation from the optimal 90° gripper angle increased damage by 1.8 % per 10° shift. Overall, proper fruit orientation reduced damage by 40 %, minimal occlusion by 36 %, and optimal illumination by 25 %. A multiple linear regression model explained the variance in damage rate (R2 = 0.924) and achieved a low RMSE of 1.85 %, demonstrating high predictive accuracy and validating the model's reliability in quantifying the influence of harvesting parameters. By investigating these aspects and exploring strategies for minimizing damage, the study aims to advance fruit harvesting robotics and contribute to the successful commercialization of this technology.

1. Introduction

The importance of damage rate in robotic orange picking extends far beyond the operational efficiency; it is fundamentally linked to the commercial success and sustainability of agricultural enterprises. While achieving a high success rate in harvesting operations is undoubtedly crucial for productivity, the quality of the harvested fruit is equally paramount. High damage rates not only result in financial losses due to spoiled or inferior-quality fruit but also tarnish the reputation of the brand or orchard. In today's discerning market, consumers prioritize not only quantity but also quality when making purchasing decisions. Fruits that are bruised, punctured, or otherwise damaged during harvesting not only result in lower prices but also face increased rejection rates from retailers and consumers alike. Therefore, minimizing damage rates is imperative not only for maximizing yield but also for ensuring the long-term viability and competitiveness of agricultural businesses in a market increasingly driven by quality and sustainability considerations.

In over more than a decade of research done on fruit harvesting robotics, most research traditionally focuses on metrics like success rate, detection accuracy, precision, F1 score and recall [1]. Deep learning methods like Convolutional Neural Network (CNN) [2 3 4 5], You Only Look Once (YOLO) [6 7 8], Single Shot Detector (SSD) [9 10] and others are commonly used for fruit detection purpose. Over time, fruit harvesting robots have achieved high accuracy and precision in detection as well as improved success rates. However, another critical factor, specifically the damage rate, frequently receives inadequate attention. Overlooking damage rate can have significant repercussions on fruit quality, market value, and advancement towards its commercialization [11]. As robotic harvesting technologies evolve, prioritizing the reduction of damage rates alongside other metrics is crucial. To date, very

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https://doi.org/10.1016/j.asej.2025.103735
Received 21 October 2024; Received in revised form 9 April 2025; Accepted 24 August 2025
Available online 1 September 2025

limited research is done on damage rate with very few analyses available in existing literature. Hence this study focuses on an in-depth study of analyzing the effects of damage rate of fruit harvested when using a fruit harvesting robot.

By understanding the factors that cause damage to fruits and their influence on damage metrics, researchers can develop more robust robotic picking systems that optimize fruit quality and harvesting efficiency under diverse conditions. The efficiency and efficacy of robotic orange picking are dependentt upon various factors, each influencing the damage rate of the harvested fruit. Foremost among these factors is the type of gripper utilized by the robotic system. End effectors come in different designs, ranging from soft, compliant type to rigid, mechanical claws. Soft grippers, often made of materials like silicone, are adept at delicately handling fruits like oranges minimizing bruising or puncturing. Conversely, rigid grippers, though efficient in firm grasp, may inadvertently damage the fruit due to excessive pressure. Therefore, the choice of gripper type significantly impacts the damage rate during the harvesting process. It is important that gripper exerts optimum force on the fruit such that it is successfully able to grasp it but avoid any damage to the fruit in the process. Fig. 1 below shows the commonly used gripper mechanisms for fruit harvesting of fruits in previous studies ranging from stem cut and grip, grasp and twist or grasp and pull using electrical or pneumatic system.

The 3-finger silicon gripper was chosen for this study on orange fruit grasping and damage rate analysis due to its superior ability to handle delicate objects without causing bruising or deformation. Unlike suction grippers, which may struggle with irregularly shaped or textured fruits, the 3-finger design provides a more secure and adaptable grip, ensuring better conformance to the orange's shape. Compared to pneumatic grippers, which often lack precision in force control, the silicon material offers a soft and compliant interface, reducing the risk of excessive pressure. Furthermore, grasp-and-cut mechanisms, while effective in harvesting, may introduce additional stress on the fruit due to cutting actions, whereas the 3-finger silicon gripper focuses solely on gentle grasping. Its versatility, combined with the ability to adjust grip strength, makes it an ideal choice for reducing damage during the handling of sensitive fruits like oranges. However, it is acknowledged that other gripper designs, with potentially enhanced performance characteristics, could be developed and tested in future studies to further optimize fruit handling and damage reduction.

Another critical determinant of damage rate in robotic orange picking is the orientation of the fruit at the point of harvest [23]. Oranges grow in various orientations on trees, and the robotic arm's approach to grasp them must be optimized to minimize damage. For instance, picking oranges at an angle that places excessive stress on the stem can result in stem detachment or tearing of the fruit's skin, leading to spoilage or reduced market value. Thus, proper attention to the orientation of the fruit during picking is essential to avoid damage. Implementing advanced computer vision systems equipped with high-resolution cameras and machine learning algorithms can enable robots to accurately detect the orientation of fruits on orchard [24]. These algorithms should not only be trained to detect quality fruit but also to ensure correct orientation of fruit is detected to avoid damage while picking. The systems can analyze visual data in real-time to determine the optimal angle for grasping each fruit, considering factors such as stem position and fruit orientation relative to the tree branches. Furthermore, implementing closed-loop feedback control systems enables the robot to continually adjust its grasping technique based on real-time feedback from sensors and vision systems. By iteratively refining its approach, the robot can optimize the orientation of the fruit at the point of harvest to minimize damage while maintaining efficiency.

Moreover, illumination plays a pivotal role in robotic orange picking, particularly in outdoor orchard environments where natural light conditions fluctuate [25]. Inadequate illumination can impede the robot's vision system, leading to errors in fruit detection and improper grasping techniques due to shadow formation. Hence, optimal lighting conditions must be maintained to facilitate accurate fruit detection and minimize damage during the picking process. Furthermore, occlusion of the fruit by leaves, branches or other fruits, poses a significant challenge to robotic orange picking systems. Occluded oranges are often difficult to detect and grasp accurately, increasing the likelihood of damage during retrieval. Advanced vision systems coupled with machine learning

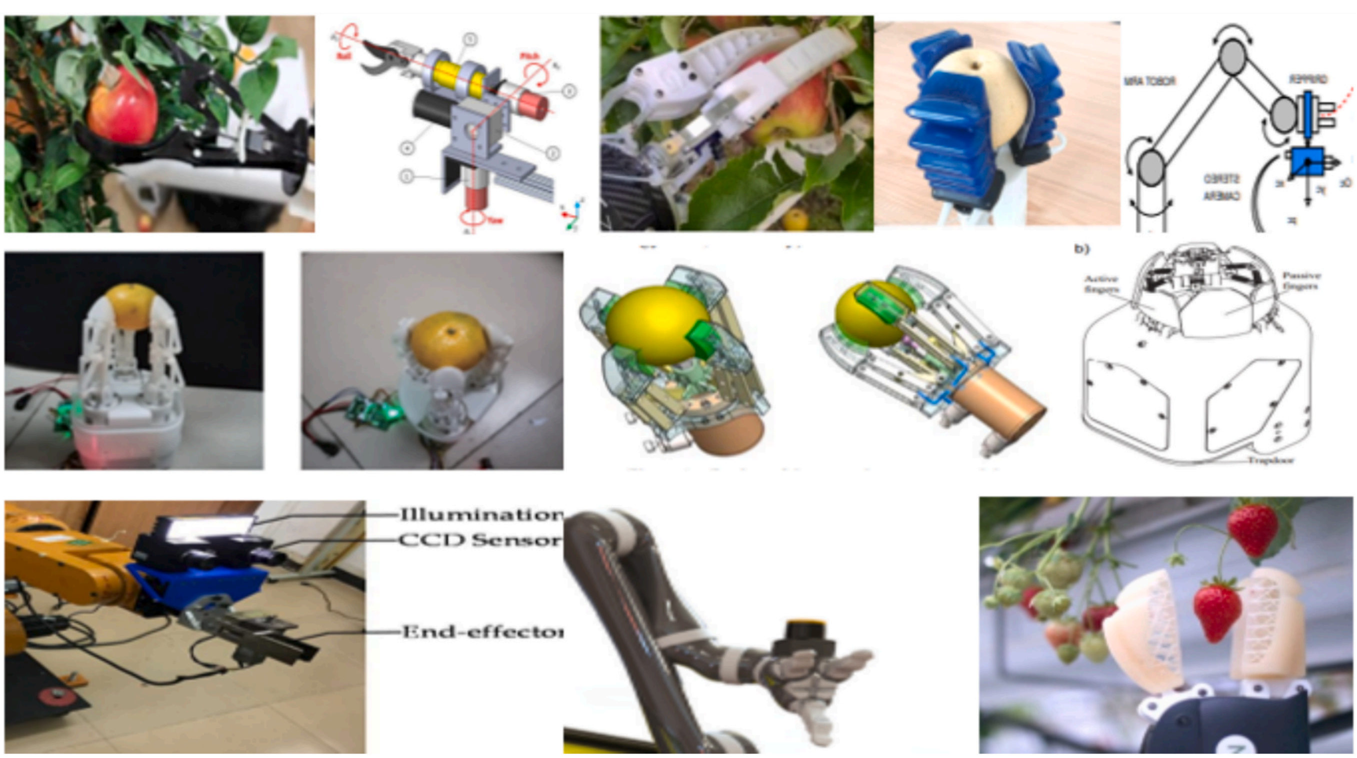

Fig. 1. Various grippers used in fruit harvesting robots {Row 1: [12,13,14,15,16] Row 2: [17,18,19] Row 3: [20,21,22]}.

algorithms that has been trained on large dataset with numerous pictures of foliage occlusion, branch occlusion and fruit occlusion can reduce this issue by enabling the robot to anticipate the presence of occluded fruit and adjust its picking strategy accordingly.

Although independent studies on this topic is very limited, some previous papers have shed light on its importance while field testing of fruit harvesting. Some studies have computed damage rate but many papers lack details like bruise type, cause and its circumstances. Table 1 shows previous studies that have determined damage rate and type of damage caused by fruit picking by the fruit harvesting robot.

This paper investigates multiple facets of damage incurred during fruit harvesting, focusing on a comprehensive examination of the reasons behind such damage within the context of fruit harvesting robots. It scrutinizes the diverse types of damage inflicted upon fruits, investigating the parameters such as the depth and diameter of bruises. Additionally, the study evaluates the impact of factors such as varying orientation, occlusion, and illumination on the extent of damage. Hence the paper covers the following gaps:

Table 1
Damage rates and damage type of fruits harvested for previous studies.

Reference	Year	Fruit harvested	Damage rate %	Types of damage	Salient features of robot
[26] Silawal et al.	2017	apple	6.3 %	Skin damage, spur damage	Gripper mechanism
[27] Zhou et al.	2023	apple	17 %	Flesh bruise	Gripper finger
[28] Bac et al.	2017	sweet pepper	13–19 %		Fin-ray
[29] Lehnert et al.	2020	sweet pepper	25 %	Skin damage	
[30] Ji et al.	2017	apple	10 %		Arc-shaped finger
[31] Mu et al.	2017	kiwi	20 %		Grasp and pull mechanism
[32] Mika et al.	2015	plum	18 %	Flesh bruise	Straddle mechanical harvester
[33] Xiong et al.	2020	strawberry	10–20 %	Flesh bruise	Cut and pick improved mechanism
[34] Goulart et al.	2023	mango	3 %		6 finger grip type end −effector
[35] Baeten et al.	2007	apple	30 %	Skin damage	
[36] Zeeshan et al.	2024	orange	6–11 %	Skin damage, Flesh bruise	3 finger silicon gripper
[37] Ren et al.	2023	strawberry	23 %	Flesh bruise	Pneumatically actuated soft gripper
[38] William et al.	2019	kiwi	26 %	Skin damage	
[39] Li et al.	2016	apple	46.7 %	Flesh bruise, Skin damage	3 finger gripper
[40] Xiong et al.	2019	strawberry	5.4 %	Flesh bruise	Cable driven gripper
[41] Parsa et al.	2023	strawberry	17 %	Bruising for failed attempts due to dropping	Gripper fingers with cutter

1. This paper highlights the critical importance of minimizing damage rates in quality fruit harvesting using fruit harvesting robots. It provides an in-depth study of the damage rates caused by fruit harvesting robots, addressing a topic that has been relatively underexplored.
2. This paper presents a comparative analysis of how orange fruit orientation, occlusion types, and illumination conditions affect damage rates during robotic picking. It further establishes a connection between specific types of bruises and their underlying causes. The findings are reinforced through multiple regression analysis, providing strong statistical support. These insights offer valuable guidance for enhancing the efficiency and precision of fruit harvesting robots.

The Section 1 of the paper highlights the significance of the damage rate while shedding light on previous studies. Section 2 mentions the methodology of study. Section 3 describes the experimental setup while Section 4 explains the types of damage rate and parameters affecting the damage rate. Section 5 analyzes the results while Sections 6 and 7 discusses and concludes the study. By emphasizing these critical aspects, this study seeks to advance the development of fruit harvesting robotics and facilitate the successful commercialization of this technology. A comprehensive understanding and reduction of damage rates have the potential to markedly enhance the performance and efficiency of fruit harvesting robots, thereby offering substantial benefits to the agricultural industry.

2. Methodology

The orange fruit harvesting robot, constructed with an aluminum body and equipped with a three-finger silicon gripper was designed to apply force less than 80 N during the gripping process. It was tested for damage rate assessment under controlled experimental conditions to ensure repeatability and minimize external variability. A total of 57 samples were tested in a controlled laboratory environment, where temperature and humidity were consistently maintained. These controlled conditions ensured that the experiments could be reliably replicated. The artificial lighting and strategically placed fruit clusters, branches, and foliage were used to simulate varying occlusion and illumination scenarios. Three primary factors were investigated: occlusion conditions, illumination conditions, and gripper orientation. Occlusion was categorized into fruit cluster occlusion, branch occlusion, and foliage occlusion, and the robot's CNN-based vision system was analyzed to determine its effectiveness in compensating for these obstructions during fruit detection and grasping. For illumination conditions, artificial shading was introduced to simulate high-light environment of 1000 Lumen/m^2 verses low-light environments of 400–600 Lumens/m^2, and the impact of shadow-induced variations on the detection and grasping efficiency of the robot was assessed. Additionally, gripper orientation and picking angles were systematically varied to evaluate their influence on bruising, with different grasping approaches tested to determine their effect on fruit damage. The severity of damage was quantified through depth and diameter measurements of bruises, recorded using a high-resolution RGB camera. Observed damage types primarily included flesh bruising and skin peeling near the stem area. To ensure the replicability and credibility of the study, each test was repeated multiple times under identical conditions, with environmental factors systematically controlled. The controlled lab conditions included consistent temperature (25 °C), humidity (60 %), and artificial lighting conditions (400–1000 Lumen/m^2). Furthermore, multiple regression analysis was conducted on the controlled trials to predict the coefficient of determination (R^2) for the model, providing a statistical measure of how well the independent variables (occlusion, illumination, and gripper orientation) explained the variance in damage rates. The experimental methodology is summarized in Fig. 2.

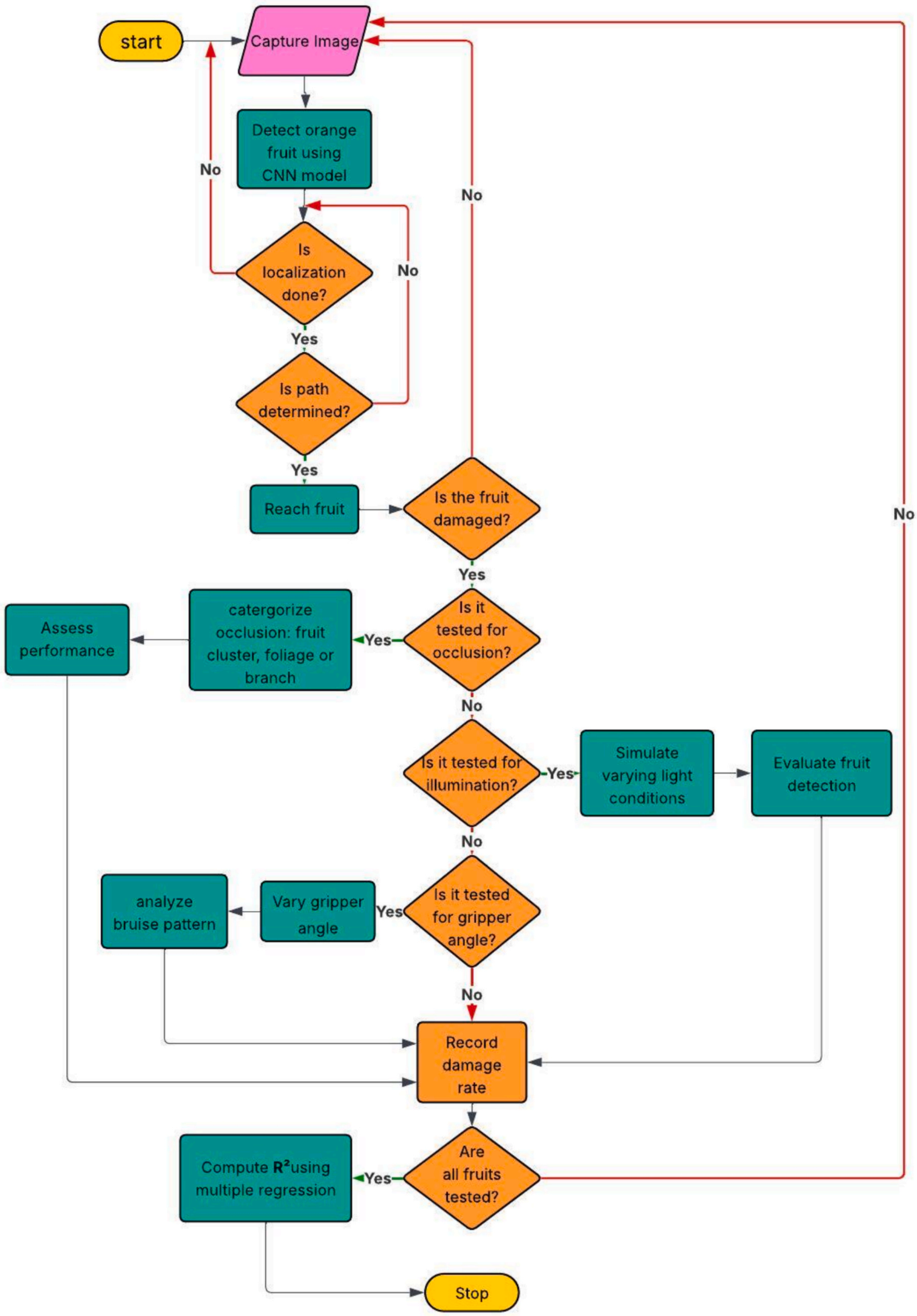

Fig. 2. Flowchart of the methodology for fruit damage analysis of fruit harvesting robot.

3. Experimental set-up

In the laboratory, an experimental setup was established to test a fruit harvesting robot equipped with computer vision capabilities as shown in Fig. 3. This setup featured a 5-degree-of-freedom aluminum robot arm controlled by a Raspberry Pi board, along with stepper motors and drivers for precise manipulation. The dimensions and design details of the robot are thoroughly discussed in the paper by Zeeshan et al. [36]. Fruit detection was accomplished using a Convolutional Neural Network (CNN) algorithm trained on a set of augmented orange fruit samples, while path planning was handled by the Rapidly-exploring Random Tree (RRT*) algorithm. The training of these algorithms was performed on 11th Generation Intel Core on a Dell workstation of i5 with 1135G7 at the rate 2.40 GHz and RAM of 8 GB, as described by Zeeshan et al. [42].

To simulate real-world conditions, various factors such as illumination, occlusion, and fruit orientation were systematically manipulated. Adjustable illumination sources represented different lighting scenarios, while occlusion was created using leaves and branches to obstruct the fruit's view, challenging the robot's detection capabilities. Additionally, fruits of different types and sizes were positioned in diverse orientations to test the robot's adaptability to various harvesting scenarios. The experimental procedure involved calibrating the camera and robot arm for accurate perception and manipulation, followed by 57 trials under different combinations of illumination, occlusion, and fruit orientation settings. The robot employed computer vision algorithms to detect, localize, and harvest the target fruit, with each trial recorded to assess the system's performance. Data analysis provided insights into the impact of each experimental variable on the robot's effectiveness in the fruit harvesting task. Table 2 shows the study parameters and the experimental conditions for the research.

The current study focuses on the damage rate analysis of orange fruit under varying conditions, including occlusion, illumination, and gripper orientation. The three-finger gripper used is designed to apply force less than 80 N during the gripping process. However, conducting similar studies for other fruits would require consideration of several factors.

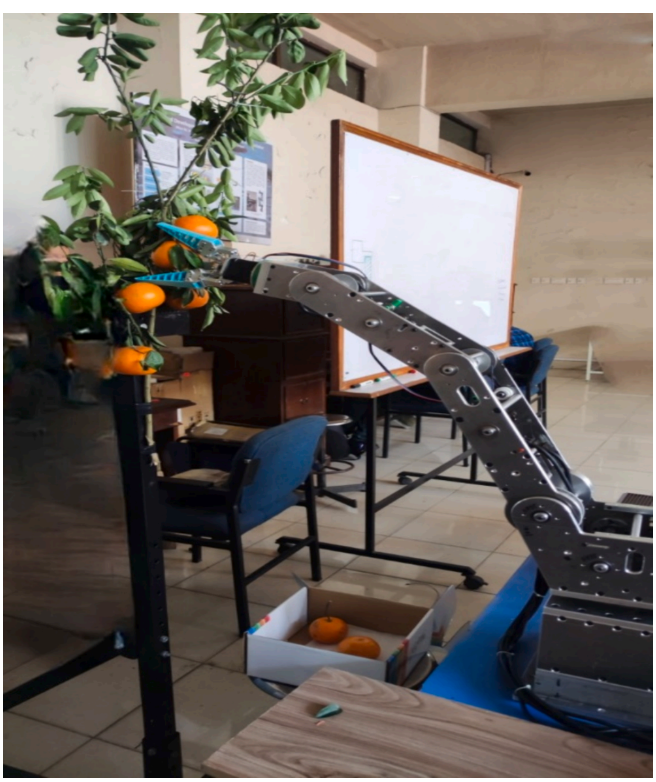

Fig. 3. Experimental set up of fruit picking in the laboratory.

Table 2
Experimental conditions and parameter specifications.

Parameter	Conditions	Measuring technique
Occlusion	None, Moderate 30–50 %, Full > 70 %	RGB-D camera + segmentation
Illumination	400, 600, 800, 1000 Lumens/m^2	Lux meter
Gripper Angle	70°, 80°, 90°, 100°, 110°, 120°	Image-based tacking

The physical properties of the fruit, such as size, shape, skin thickness, firmness, and ripeness, significantly influence damage susceptibility. Environmental and handling conditions, including occlusion types, illumination variations, gripper type and the applied force by the gripper must be tailored to the specific fruit's characteristics.

Damage rate is computed and analyzed for fruit picked from different orientations, occlusions and varying illumination. The type of damage caused from occlusion is analyzed. The bruises caused from fruit picking through fruit harvesting robot is studied for its diameter and depth. Overall, damage rate is computed for the orange picking using fruit harvesting robot using the formula below.

Damage Rate (%)= (Total Number of Harvested Fruits/Total - Number of Damaged Fruits) × 100

4. Fruit damage types

Two main types of bruises are noted in the study. One is skin bruise that causes a dent with a certain depth and diameter. This is caused mainly due to impact by gripper force on the fruit. Unlike successful picks, this excessive force on fruit is caused by wrong orientation of the fruit pick or slipping of fruit from gripper due to improper grip of fruit by the fruit harvesting robot. The other type of bruise is skin peel. This results in the peeling of skin of orange near the stem area of the fruit. This is again due to improper pull exerted on the fruit due to wrong orientation as a result of occlusion or poor illumination. Fig. 4 below shows type of bruises noted while picking fruit using fruit harvesting robot.

4.1. Gripper orientation

To avoid fruit damage, it is important and most desirable to have end-effector position perpendicular to the face of the fruit. The soft silicon gripper imposes optimum force in this position and grips the fruit properly without causing damage. As the angle of orientation of gripper deviates from the perpendicular position, the quality of grip may decrease causing the fruit to fall causing bruising, as seen Fig. 4(b) above. Furthermore, the force exerted on the fruit causes gripper scar marks as shown in the Fig. 4(a) above. Gripping from an improper angle may also result in fruit being gripped near the steam causing skin peel as can be seen in Fig. 4(c). Fig. 5 shows the various orientations for fruit picking used in the study to analyze effect of orientation on damage rate through fruit harvesting robot.

4.2. Fruit occlusion

There are three types of occlusions observed on the fruit orchard. These are occlusion due to foliage, branches and other fruits. Fig. 6 shows these occlusions that occur in real-time fruit picking. Training on real-time dataset helps to improve fruit detection of the algorithm. The bigger the dataset and the more variety of images of occlusions present in the dataset, the better shall be the detection ability of the algorithm, resulting in proper coordinate detections and hence lesser damage rate.

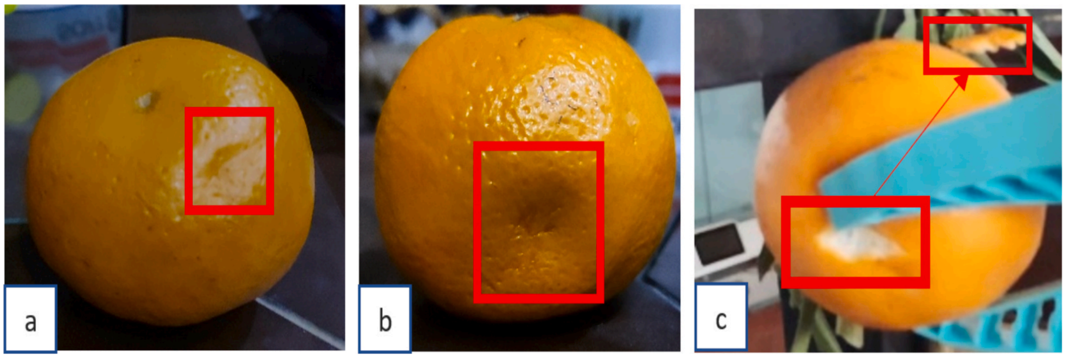

Fig. 4. Skin bruise and skin peel after fruit picking from fruit harvesting robot.

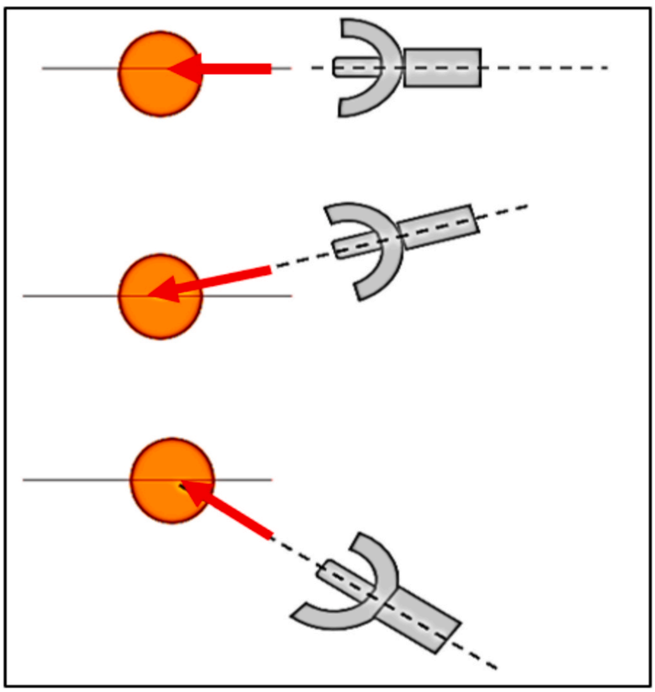

Fig. 5. The gripper orientations to study damage rate of fruit harvesting robot.

4.3. Varying illumination

Proper illumination improves visibility for fruit detection and improves accuracy of fruit detection with correct coordinates. Poor illumination result in shadows and although the fruit may be detected, the coordinates selected for picking may not be the best suited coordinates for the fruit picking. Fig. 7 shows a comparison of the visibility of orange fruit in orchard due to varying illumination. Testing was conducted for poor illumination of 400–600 Lumens/m^2 and for good illumination of 1000 Lumens/m^2 to compare damage rates.

5. CNN-based computer vision model for fruit detection

The CNN model used in this study has been specifically trained to handle occlusion and varying illumination conditions. To address occlusion, data augmentation techniques such as flipping, rotation, random cropping, shifting, and illumination variation were employed to increase the diversity of the dataset. This approach exposed the model to partial occlusion patterns during training, enhancing its ability to detect fruits even when partially obscured. Additionally, the model's multi-scale feature extraction capability enables it to focus on both visible and partially occluded regions of the fruit. For illumination variability, the model was trained on a diverse dataset that included images captured under different lighting conditions, allowing it to learn illumination-invariant features. Pre-processing techniques such as color normalization and histogram equalization were also applied to further enhance the model's robustness against lighting fluctuations.

The CNN architecture consists of multiple convolutional layers, maxpooling layers, and dropout layers, designed to extract key features while minimizing overfitting. Hyperparameters, including batch size,

Fig. 6. Types of occlusions in orange orchard: foliage occlusion, fruit occlusion and branch occlusion. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 7. Comparison of varying illumination causing shadows in poor illumination.

number of hidden layers, and learning rate, were optimized through extensive tuning to achieve high accuracy in fruit detection. The CNN model was trained with a batch size of 64, utilizing 4 hidden layers with 128 neurons per layer. The optimization technique used was RMSprop, with ReLU activation and cross-entropy loss. Convolutional layers had 64 filters with a kernel size of 3 × 3. The results demonstrate that the model achieved a precision of 98.1 %, followed by a recall of 94.8 %. The accuracy of the orange detection was 93.8 %, and the F1 score reached 96.45 %. These results demonstrate that the model is highly effective in detecting and localizing oranges, even under challenging conditions such as occlusion and varying illumination. Fig. 8 shows the CNN model performance after training, demonstrating its effectiveness in detecting and localizing oranges under varying conditions of occlusion and illumination.

These evaluations confirm that the CNN effectively compensates for occlusion and illumination challenges, ensuring accurate detection and handling of fruits during harvesting operations. The model's ability to detect fruit locations, even in the presence of occlusions or lighting variations, contributes to reducing damage and improving efficiency in fruit harvesting systems.

6. Experimental results

Bruise diameter and bruise depth was computed for each damaged fruit for varying orientation, occlusion and illumination. A box plot in Fig. 9 shows an average bruise diameter of 14 mm for the above study and average bruise depth of 5 mm. These measurements provide a quantitative assessment of damage severity, offering critical insights for the study of fruit harvesting processes and the optimization of harvesting techniques.

The studies found that the less damage was done to fruit when picked at gripper angle perpendicular to fruit. Out of a total of 57 fruits, only 5 showed damage in perpendicular gripper orientation, while 11 fruits were damaged due to wrong orientation. Further, the bruise diameter and depth of wrong orientation were bigger as compared to the perpendicular gripper orientation. Figs. 10 and 11 shows the picking of fruit perpendicular and at an angle from robot gripper. Fig. 12 compares the fruits damaged when picked perpendicular and at an angle from robot gripper.

Fig. 13 shows testing done to assess damage type and rate due to occlusion of orange fruit. It was observed that from testing on 57 fruits on occluded fruit picking, 11 fruits got damaged due to skin peel and 9 fruits got damaged due to skin bruise due to occlusion.

Fig. 14 shows the type of damage caused by occlusion in the orange fruit picking process by fruit harvesting robot. A significant portion of the damage was caused by skin peel, with skin bruise also being a common result of occlusion during the harvesting process.

It is observed that out of a total of 57 fruits picked, 17 showed damage in poor illumination while only 10 showed damage in proper illumination. Fig. 15 shows the damage rates of fruits in varying illumination.

Fig. 16 shows collective results of damage rate reduction by deployment of proper illumination, minimal occlusion and picking fruit by placing gripper perpendicular to the fruit. This is verified by the multiple regression study mentioned in Section 7.

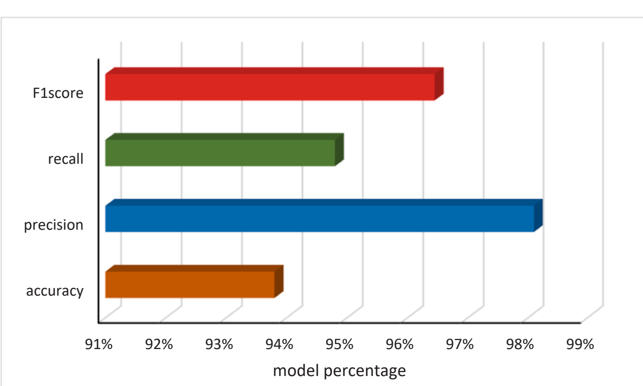

Fig. 8. CNN model performance for orange harvesting robot [42]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

7. Multiple regression and statistical analysis

The experimental setup was designed to statistically analyse the damage rate in fruit harvesting using multiple regression. Damage rate, Y, was measured as a function of three independent variables: occlusion, X_1, illumination, X_2, and the gripper angle, X_3. A series of controlled trials were conducted under varying conditions of these parameters, and the corresponding damage rates were recorded. The 3D scatter plot in Fig. 17 illustrates the relationship between occlusion percentage, illumination (Lumens/m^2), and gripper angle (degrees). Each point in the plot represents a data entity, providing a visual representation of how these factors vary in relation to one another. The three-dimensional view enables an assessment of potential trends, or patterns in the dataset. The collected data was analysed using multiple linear regression to establish a predictive relationship of the form:

$$Y = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_3^2 + \in$$

where Y is the damage rate (%), X_1 is percentage occlusion, X_2 is the illumination in Lumens/m^2, X_3 is the gripper angle (°), b_o is the intercept

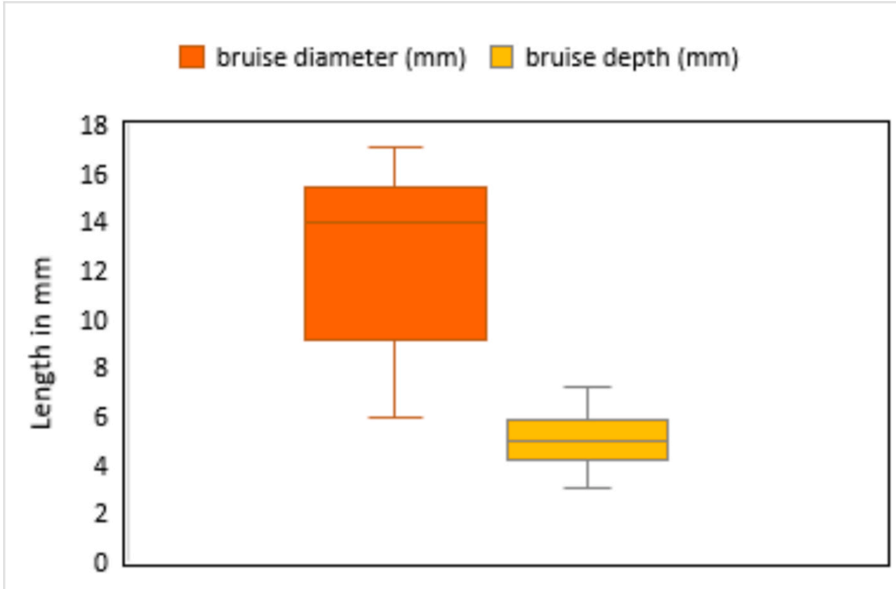

Fig. 9. Box plot showing bruise diameter and bruise depth of damaged fruit via fruit harvesting robot.

Fig. 10. Picking of fruit using fruit harvesting robot gripper perpendicular to base of fruit.

when all predictors (b_1, b_2, b_3 and b_4) are zero, b_1, b_2, b_3 and b_4 are the regression coefficients quantifying the effect of occlusion, illumination, gripper angle linear and gripper angle quadratic, respectively while ε is the error term.

The regression coefficients were estimated using the least squares method. The least squares method minimizes the sum of squared residuals, which represent the differences between actual and predicted values. This approach ensures the derivation of the best-fitting regression coefficients, optimizing the accuracy of predictions.

$$b = (X^T X)^{-1} X^T Y$$

The confidence interval (CI) of a regression coefficient is given by:

$$CI = b \pm t_{\alpha/2}.SE(b)$$

where b represents the estimated regression co-efficient, SE(b) represents the standard error of the coefficient and $t_{\alpha/2}$ represents the t-critical value from the t-distribution at a significance level α. This statistical analysis facilitated the identification of significant predictors influencing fruit damage and provided a reliable model for estimating damage rates under different harvesting conditions.

Model performance was evaluated using the coefficient of determination (R^2), which quantifies the proportion of variance in the dependent variable explained by the independent variables:

$$R^2 = 1 - \sum (Y_{actual} - Y_{predicted})^2 / \sum (Y_{actual} - Y_{mean})^2$$

The statistical significance of each predictor was evaluated using p-values, with a significance level of $\alpha = 0.05$, indicating a 5 % risk of Type I error. Additionally, a 95 % confidence interval was calculated for each regression coefficient to estimate the range within which the true value is likely to fall. The highly significant F-statistic ($F = 285.6$, $p < 0.001$) confirms the overall statistical significance of the model. All predictor variables show statistically significant effects ($p < 0.01$): occlusion exhibits a positive linear relationship ($\beta = +0.118$ per 1 % increase), illumination demonstrates a protective negative linear effect ($\beta = -0.105$ per Lumen/m^2), and gripper angle displays a quadratic relationship with a significant U-shaped pattern (linear term $\beta = -0.18$ per degree, quadratic term $\beta = +0.0018$). The 95 % confidence intervals for all coefficients exclude zero, further supporting their statistical and practical significance. These results suggest that fruit damage can be effectively minimized by reducing occlusion, increasing illumination, and maintaining gripper angles close to 90°, with the model providing reliable predictions within the tested ranges.

Table 3 below shows the co-efficient for each predictor and their respective p values. The regression analysis reveals that occlusion, illumination, and gripper angle significantly influence the predicted damage rate. An increase in occlusion percentage is associated with a rise in damage, with approximately 1.18 % more damage observed for every 10 % increase in occlusion. In contrast, higher illumination levels contribute to reduced damage; specifically, a 100 Lumen/m^2 increase in lighting results in a 10.5 % decrease in predicted damage. The gripper angle also plays a critical role, where each 10° deviation from the optimal 90° angle leads to an estimated 1.8 % increase in damage. Furthermore, the quadratic term for gripper angle suggests a U-shaped effect, indicating that both lower and higher deviations from 90°

Fig. 11. Picking of fruit using fruit harvesting robot gripper at an angle.

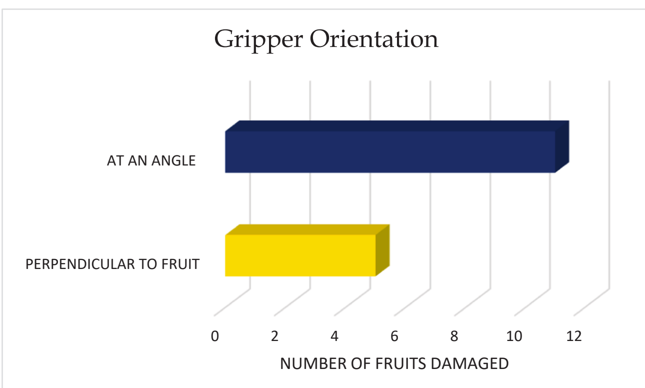

Fig. 12. Damage to fruit caused by varying gripper orientation of fruit harvesting robot.

contribute to increased damage, thereby discouraging extreme gripper angles. This study, which examined the factors influencing mechanical damage during robotic orange harvesting, establishes that maintaining fruit orientation perpendicular to the gripper surface results in an approximate 40 % reduction in damage rate. Increased levels of occlusion were associated with a 36 % rise in damage, while enhanced illumination conditions contributed to a 25 % reduction. These findings highlight the critical role of precise fruit positioning, visibility, and optimal lighting in minimizing harvest-induced injury, and provide essential insights for the development of more effective and gentle robotic gripper systems.

Fig. 18 shows the predicted damage rate verses actual damage rate for the three predictors mentioned above. This figure helps in visually assessing the model's performance by illustrating how closely the

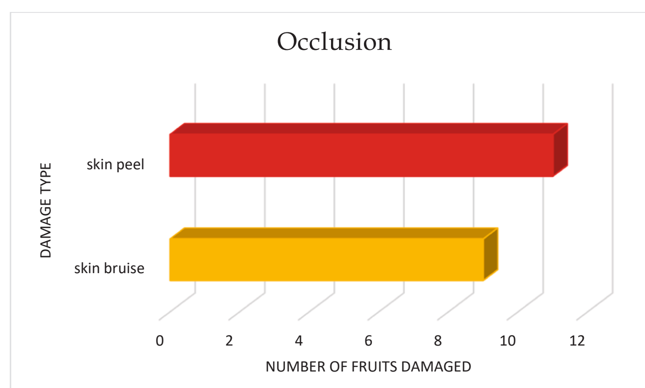

Fig. 14. Types of damage caused due occlusion of fruits, leaves and branches by fruit harvesting robot.

Fig. 13. Testing of picking of fruits in occluded environment.

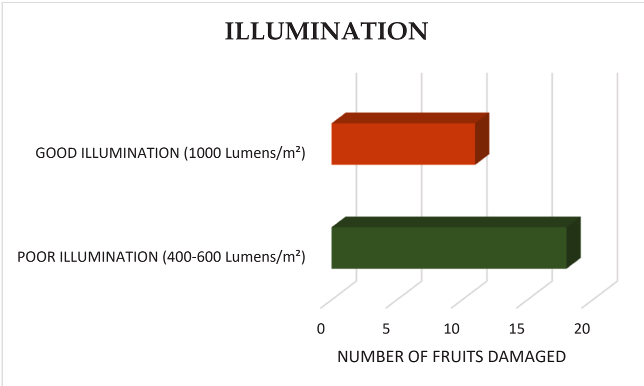

Fig. 15. Number of fruits damaged using fruit harvesting robot by varying illumination.

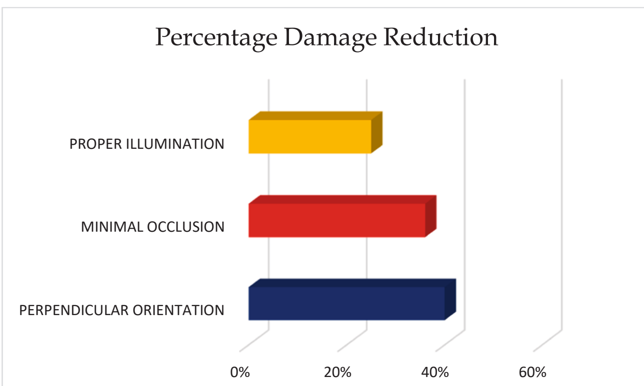

Fig. 16. Damage rate reduction by perpendicular gripper orientation, proper illumination and minimal occlusion.

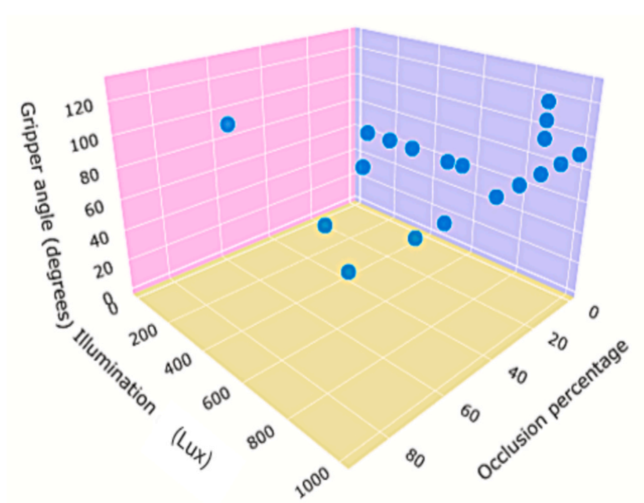

Fig. 17. Scatter plot displaying relationship between occlusion percentage, illumination (Lumens/m^2), and gripper angle (degrees).

predictions align with the actual values. The multiple linear regression model indicates 92.4 % of the variance in the damage rate percentage (R^2 = 0.924), indicating a strong fit. RMSE is 1.85 % suggests high predictive accuracy, with damage rate estimates deviating from observed values by 1.85 % on average.

Table 3
Regression coefficients and p-values for key predictors in the model.

Predictor	Co-efficient	P-value
Occlusion	+0.118	<0.001
Illumination	−1.05	<0.001
Gripper angle linear	−0.18	<0.001
Gripper angle quadratic	+0.002	0.002

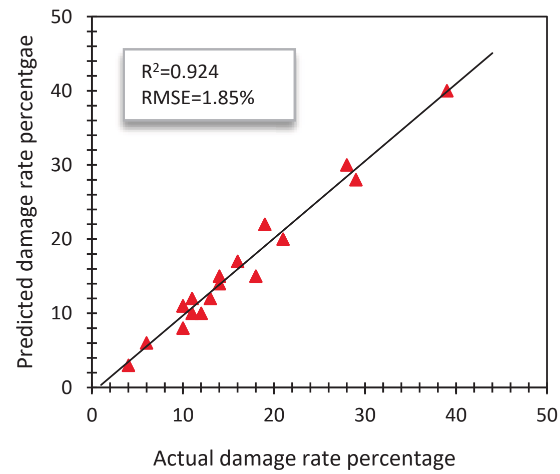

Fig. 18. Model performance for damage rate percentage for orange fruit picking. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

8. Discussion

It has been found that the quality of picked fruit can be enhanced, consequently minimizing damage rates, by considering certain factors when employing fruit-picking robots. Initially, computer vision detects the orange and delineates a bounding box around it. The robot's path planning must ensure that it picks the fruit with the gripper axis perpendicular to the fruit's face. Studies indicate that minimum damage occurs when the orientation is perpendicular, compared to when fruits are picked at an angle. This can be ensured through improved path planning, aligning the coordinates of both gripper and fruit exactly perpendicular. In real-world scenarios, achieving exact perpendicular detection and reach is not always feasible due to occlusion by foliage, branches, and other fruits. However, during fruit picking, detection of the most suitable fruit surface and orientation of pick can be ensured with improved computer vision algorithms and advance path planning algorithms. Furthermore, reducing damage rates due to occlusion can also be achieved through better real-time training datasets of orange fruits, including a variety of occluded fruit pictures from different orientations to improve algorithmic detection.

Additionally, picking the fruit from the right angle is essential to avoid skin peeling and maintain fruit quality. Currently, computer vision algorithms primarily focus on correctly detecting quality fruit, yet it's equally important to identify the correct orientation for picking. This aids in determining the right coordinates for path planning to approach the fruit correctly. Improved illumination also decreases damage rates by reducing shadows and enhancing fruit detection. In real-time fruit-picking scenarios, shadows and poor illumination may occur due to varying weather conditions, but this issue can be mitigated by implementing backup illumination for consistent fruit detection.

The present study demonstrates significant reductions in fruit damage through optimized harvesting conditions, with perpendicular orientation yielding a 40 % reduction, minimal occlusion resulting in a 36 % reduction, and proper illumination contributing to a 25 % reduction in damage. These findings align well with existing literature. Zhang et al. [43] reported a decline in harvesting success rate from 82.4 % to 65.2 % due to occlusion caused by foliage and branches, highlighting the critical role of visibility. In comparison, our findings show that minimal occlusion not only enhances detectability but also reduces incidence of skin peeling during the grasping phase, especially when using a soft gripper. Gong et al. [44] observed a 7.6 % improvement in occlusion detection accuracy under lighting conditions between 1000 and 1200 lm/m^2, corroborating our results where damage was reduced from 18 fruits (under poor illumination) to 11 fruits when illumination was 1000 lm/m^2. Arad et al. [45] also reported enhanced fruit detectability under controlled lighting, achieving a precision rate of 95 % using deep learning models. In terms of end-effector positioning, Magistri et al. [46] demonstrated that optimal grasp point alignment increased picking success by 18.5 %. Similarly, our study shows a reduction in damaged fruits from 11 (under improper grip angles) to only 5 when fruits were approached at a perpendicular orientation, underscoring the importance of correct gripper angle. These results collectively affirm that improper gripper orientation, occlusion caused by foliage, branches, or neighbouring fruits, and inadequate illumination substantially increase the damage rate in robotic fruit harvesting. Therefore, future optimized studies should focus on refining gripper alignment, enhancing visibility under occluded conditions, and implementing adaptive lighting to improve harvesting performance and fruit integrity.

While this study primarily investigates the impact of gripper angle on damage rates during the grasping of oranges, exploring alternative gripper designs could yield further improvements in reducing damage. Specifically, the use of materials such as soft silicones with varying hardness or rubberized coatings may reduce the likelihood of bruising by better conforming to the shape of the fruit and absorbing impact forces. Additionally, adaptive multi-fingered or multi-pad gripper designs could provide more even distribution of forces, minimizing localized pressure and minimizing damage risks. The integration of force-sensing mechanisms, like a tactile sensor, would allow for real-time adjustments in grip strength, ensuring that the applied force is always optimized according to the object's firmness, thus preventing excessive pressure. Furthermore, exploring alternative gripper geometries, such as hybrid pneumatic-mechanical systems, could enhance compliance and adaptability, further reducing the risk of damage. Future research could benefit from investigating these hardware improvements to provide a more comprehensive understanding of how gripper design influences damage reduction during object handling.

The findings of this study, while significant in the context of orange harvesting, given that oranges are among the widely cultivated and consumed fruits globally, may not be directly applicable to other fruit types due to differences in harvesting dynamics. Fruits such as apples, peaches, or berries exhibit distinct variations in texture, size, and firmness, which influence the gripping requirements and the potential for damage. The softer or more irregular shapes of certain fruits may necessitate the development of alternative gripper designs or modifications in force control to reduce bruising or deformation. Additionally, the optimal harvesting mechanisms, including the angle of approach and distribution of gripping force, may vary based on the fruit's fragility or sensitivity to pressure. However, the proposed model and design approach could be extended to fruits with physical characteristics similar to oranges, such as lemons, limes, or grapefruits, which share comparable peel toughness, roundness, and firmness. In such cases, only minimal adjustments in gripper size or surface curvature may be required. For softer or high-asymmetry fruits, more substantial adaptations—such as compliant materials, tactile feedback systems, or shape-conforming end-effectors—would be necessary to ensure gentle handling. Consequently, future research should investigate the performance of various gripper designs across a wider range of fruit types to assess broader applicability and optimize the handling of diverse agricultural produce.

This study provides a comprehensive analysis of the impact of damage rates during orange harvesting by a robotic system, focusing on factors such as occlusion, illumination, and gripper angle, all evaluated under controlled conditions. While the study highlights the significance of these parameters in minimizing fruit damage, it is acknowledged that real-world deployment involves additional complexities, such as varying field conditions, and environmental factors like wind, rain, and temperature fluctuations. These variables may influence the performance of the harvesting system. However, the insights gained from the controlled environment lay a critical foundation for future work, which can extend these findings to field testing. Such tests would assess the adaptability and robustness of the robotic system under diverse and dynamic conditions, further validating its scalability and operational efficiency for real-world agricultural applications.

Ultimately, while metrics like success rate, accuracy, precision, and recall are important in evaluating fruit-picking systems, the quality of the harvested fruit is equally critical. Damage rates, a frequently overlooked aspect, remain a significant barrier to the widespread commercial use of fruit harvesting robots, despite more than a decade of research. Addressing fruit damage is key to realizing the full potential of these systems in real-world applications.

9. Conclusion

- The importance of fruit harvesting robots has been well established over the years. Minimizing damage rates during robotic fruit picking is crucial for operational efficiency and the commercial success of agricultural enterprises, as it directly affects fruit quality, financial outcomes, and brand reputation. High damage rates result in financial losses and increased rejection by retailers and consumers, making quality control essential for long-term sustainability and competitiveness.
- This study emphasizes the significance of reducing damage rates in quality fruit harvesting using robotic systems. It provides an in-depth analysis of the damage caused by fruit harvesting robots and compares the impact of different fruit orientations, occlusion types, and illumination conditions on damage rates. The study also correlates bruise types with their causes, offering insights to enhance the efficiency of robotic fruit picking.
- Occlusion, illumination, and gripper angle significantly impact fruit damage during robotic harvesting. A 10 % increase in occlusion raises damage by 1.18 %, while a 100 $Lumen/m^2$ increase in illumination reduces damage by 10.5 %. Deviation from the optimal 90° gripper angle increases damage by 1.8 % per 10° shift, with extreme angles further amplifying harm. Overall, proper fruit orientation reduced damage by 40 %, minimal occlusion by 36 %, and optimal illumination by 25 %.
- The multiple linear regression model demonstrated strong predictive power, explaining 92.4 % of the variance in damage rate (R2 = 0.924) and achieving a low RMSE of 1.85 %, which indicates high predictive accuracy. This close alignment between predicted and actual damage rates validates the model's reliability in assessing the impact of key harvesting parameters.
- By highlighting these crucial aspects, this study aims to drive advancements in fruit harvesting robotics and support the successful commercialization of this technology. Understanding and reducing damage rates can significantly improve the performance and efficiency of fruit harvesting robots, ultimately benefiting the agricultural industry.
- Future research should explore alternative gripper designs, including soft materials, adaptive multi-fingered systems, and force-sensing mechanisms, to improve damage reduction in fruit harvesting. Additionally, the performance of these designs across a wider range of fruit types, with varying sizes, shapes, and firmness, should be assessed to optimize handling and minimize damage rates in diverse agricultural produce. Furthermore, real-time testing in field conditions should be conducted to evaluate the adaptability and

effectiveness of these designs under dynamic environmental factors, ensuring their practical viability for large-scale deployment.

CRediT authorship contribution statement

Sadaf Zeeshan: Validation, Formal analysis, Writing – review & editing, Methodology, Conceptualization, Writing – original draft, Investigation. **Tauseef Aized:** Investigation. **Fahid Riaz:** Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The authors express their gratitude for the grant provided by the Punjab Higher Education Commission, Punjab, Pakistan, which supported this research. The grant is referenced under letter PHEC-PICRA-20168-5.

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